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A NEW METHOD FOR ANALYSING FINANCIAL DAMAGES CAUSED BY GRID FAULTS ON INDIVIDUAL CUSTOMERS

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ABSTRACT

Disruptions in electricity supply can cause significant social and economic damages to individual customers connected to the electricity grid, causing loss of income, productivity, and material damages. In this context, considerable investments are required for improving the reliability of the electricity network, and appropriate methods are needed for evaluating the cost-benefit of such investments. This paper proposes a new method for analysing financial damages caused by loss of electricity supply for individual customers, consisting of (i) a model for representing individual customers and their grid connection, and (ii) a method for expressing the reliability of a grid connection in terms of financial damages caused by the loss of electricity supply, defined as Customer Outage Cost, CCOST. These two proposed approaches are combined in a probabilistic method for evaluating the economic impacts of grid faults on individual customers. Representing grid reliability in financial terms supports the decision-making process of improving the reliability of electricity supply. The methodology is tested with a case study for a rural dairy farm in Finland, where two alternatives for improving the reliability of electricity supply are evaluated: investments in underground cables and in a microgrid, including a cost-benefit analysis of these investments against their yielded reduction in CCOST. The results from the case study show that the proposed methodology appropriately represents an individual customer and its grid connection reliability. In the context of this study, the microgrid approach was the most cost-effective alternative to mitigate the customer damages incurred by grid faults.

INTRODUCTION

Interruption in electricity supply is a major disruptor in the functioning of societies [1]. Although large outage events bring attention to the grid resilience against large-scale natural disasters, the impacts on people's safety, health, and overall region economy do not come only from long-lasting disruptions. Minor events also have the potential to cause significant damage at the distribution network level. They can damage appliances, disrupt economic activities, and reduce well-being.

The assessment of the impacts caused by electricity supply disruptions are usually described in terms of general grid indices, such as the System Average Interruption Frequency Index (SAIFI) and the System Average Interruption Duration Index (SAIDI). These indexes are typically given as an indication of the average electricity supply reliability either on a grid level, providing an indication to Distribution System Operators (DSO) on their network reliability, or at a national level [2].

The availability of electricity supply from a customer perspective is typically expressed through indices such as the Customer Average Interruption Duration Index (CAIDI) and Customer Average Interruption Frequency Index (CAIFI). The amount of energy lost on average at the consumer side is described by the Expected Energy Not Served (EENS), typically expressing in MWh how much energy is lost due to grid unavailability over one year.

The responsibility of assessing and improving electricity supply reliability typically falls over the DSO, and requirements on reliability levels come from policy and regulations. Reliability of electricity supply can be improved by grid investments, with redundant lines and renewed infrastructure, such as underground cables. These investments tend to be costly, with overhead lines requiring a large right-of-way, while underground cabling has high initial costs and requires excavation through existing civic infrastructures.

Microgrids with islanding capabilities are an interesting alternative for grid investments, especially for disaster management [3]. Although microgrids are a well-researched topic [4–7], their widespread implementation has not so far materialized [8], mostly since the implementation of a microgrid also incurs a considerable initial investment.

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Much research has been conducted on the reliability of microgrids and the impacts of distributed generation for customer reliability in the recent years [9–13].

Despite the importance of identifying the cost-effectiveness of reliability improvements, there are currently no established methods for comparing the financial costs against the yielded reliability gains from investments in grid infrastructure or in microgrids for single-point customers. Furthermore, existing methods for assessing individual customer reliability also fail to appropriately address the growing penetration of distributed energy generation and storage at the customer side.

This paper addresses this gap by proposing a new approach for the reliability analysis of grid-connected customers, expressing reliability in terms of the financial damages to the customer caused by interruptions in electricity supply. This approach adapts a technique typically used for large-scale power systems [14], consisting of modelling a single load point and its grid connection as a load-generation unit pair. This model is applied in a probabilistic method, implemented as a Monte Carlo simulation, to calculate the total Customer Outage Cost (CCOST) associated to grid outages.

The proposed approach provides a clear indication of the financial benefit yielded from a reliability increase. By comparing the financial damages with investment costs for reliability improvements, extensive cost-benefit analysis (CBA) can be performed for investments in grid infrastructure versus in a microgrid. Moreover, this method enables the inclusion of local energy resources in the analysis, addressing the reliability benefits from a local microgrid, a particularly important assessment for rural grid-connected customers.

The paper tests the proposed approach with a case study from Finland. The costs and benefits of two alternative options, namely underground cables and a microgrid solution, are compared to improve the reliability of supply for an individual customer.

This paper is organised as follows. Section II presents the methodology in detail, describing the modelling approach and the probabilistic method used for assessing a single-point rural customer's reliability. Section III describes the case study analysed in this paper. The results from this application are shown and discussed in Section IV. Section V concludes the paper providing further discussions on the methodology and results.

METHODOLOGY

This section discusses the proposed methodology in three stages: (i) a modelling approach for a single customer (as a simple consumer or as a microgrid) and its grid connection; (ii) definition of the indices for expressing grid reliability in financial terms from a customer perspective; and (iii) the implementation of this model on a probabilistic method for calculating relevant reliability indices. Figure 1 shows how these stages are related in the proposed methodology.

Single-Point Rural Customer and Grid Connection Models

In this paper, an individual customer and its grid connection are represented as a single load-generation unit pair, adapting a methodology traditionally used in power system capacity adequacy studies. This approach consists of representing all generation connected in a power system by a single generating unit, and the total system load by a single load point [15]. By redefining the power system boundaries to a single customer and its grid connection, probabilistic methods traditionally applied for large power systems can be implemented at the individual customer level.

The reliability of supply for individual customers in the electricity grid is typically addressed in the Distribution Hierarchical Level (HL3) as the reliability of the distribution network to which the customers are connected [16]. This is not always representative of the availability of electricity supply for individual customers. The proposed modelling approach surpasses this challenge by enabling the assessment of capacity adequacy and reliability for specific individual customers. Figure 2 shows the application of this modelling approach for an individual customer and their connection to the distribution grid.

This modelling strategy supports the expansion of the grid model as multiple generating units, expressing the reliability of different grid sections. The modelling strategy is suitable for individual customers of any consumption range. Distributed generation can also be added at the customer side, and other dispatchable generators can be included and modelled with their correspondent outage probability, making for an easily expandable modelling approach. However, only the grid connection is represented in the proposed model shown in Figure 2, as this paper focuses on the effects when grid connection is lost.

The model is based on data about the grid availability, occurrence of outage events, and on data about consumer behaviour and demand, data which is typically easily available. Sufficient amount of high-quality data is needed for a proper representation of the customer grid availability. In this paper, the analysis is performed over a period of one year (typical period for reliability studies), hence modelling both the generating unit and the load point as 8760 hourly values. Higher resolution data could be used, depending on the requirements set by the customer type.

The details of the modelling strategy for the grid as a generating unit and the customer demand as a single load point is discussed in the

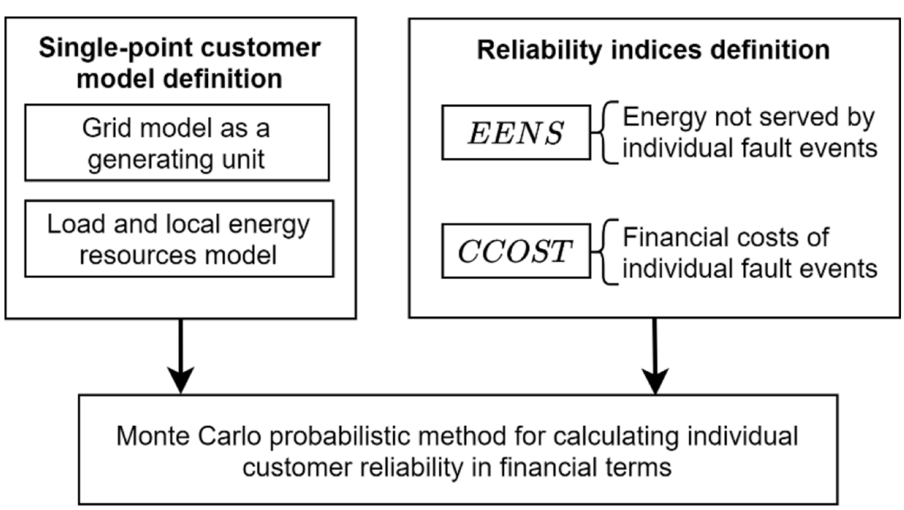

Figure 1. Summary and relationship between the proposed definitions in Section 2

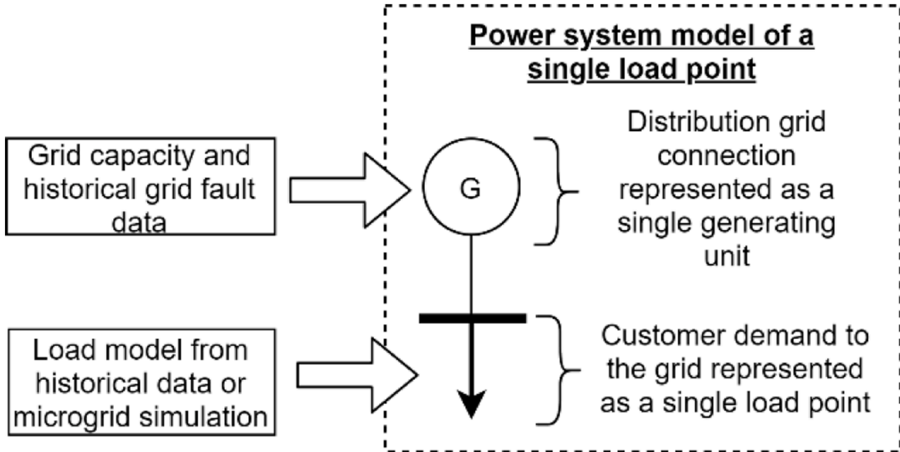

Figure 2. Proposed load-generation unit pair for an individual customer and their grid connection.

following subsections.

Generating Unit Model

Modelling the grid connection as a generating unit requires calculating its availability and available generation capacity. The available grid capacity is simply considered as the customer's demand in each time-step of year (and zero during outage events), while the grid availability is based on the number of outage events, their starting times, and their duration. Considerations on contingency measures for the distribution grid are outside the scope of this paper, and are not taken into account in the proposed modelling approach.

The number and starting moment of outage events is estimated from historical data. The average number of faults that affect a single customer per year, N_{faults}, is obtained from general indices such as CAIFI, or calculated for an individual customer from historical data. The fault starting hour probability array p_{fsh} indicates the probability of an outage event starting at each time-step of the year, given that an outage event will occur.

The grid Unavailability (U) array is obtained from multiplying the probability array p_{fsh} and the average number of faults N_{faults}. It is an array that expresses the likelihood that a fault would occur in each time-step of the analysis, leading to a loss of supply from the grid connection. With a method to accurately express the likelihood of outage events to occur at each time-step, the likely duration of each outage event needs to be considered next.

The duration of an outage event plays a critical role in determining the financial impacts caused by such event. The fault duration probability p_{fd} is defined as the probability that a fault has a duration within different defined intervals, ranging from 1 second to over 120 hours. p_{fd} is obtained from historical data to indicate the likely duration of each outage event. In the approach of this paper, a simplified assumption is considered that fault durations are statistically disconnected from fault starting times.

The *grid status array* expresses if grid is available or not. It is calculated from combining the grid Unavailability and the fault duration probability. This array indicates whether an outage event is happening or not in each time-step of a simulation *i*. Either a fault status or a normal operation status is randomly assigned to each time-step, according to the time-step's associated Unavailability. In case a fault is assigned to a time-step, the fault's duration is randomly assigned according to the historical fault duration probability p_{fd}. Subsequent time-steps are then assigned as faults according to the given fault duration. A number of *grid status arrays* must be created to properly address the stochastic nature of grid outage events. Figure 3 shows the process of creating a *grid status array* for a simulation *i* from the historical outage events dataset.

Load Model and Microgrid Operation

The load model is represented by an array of values representing the customer demand for each hour of a typical year. This paper assumes 8760 hourly values for the analysis of customer reliability over the

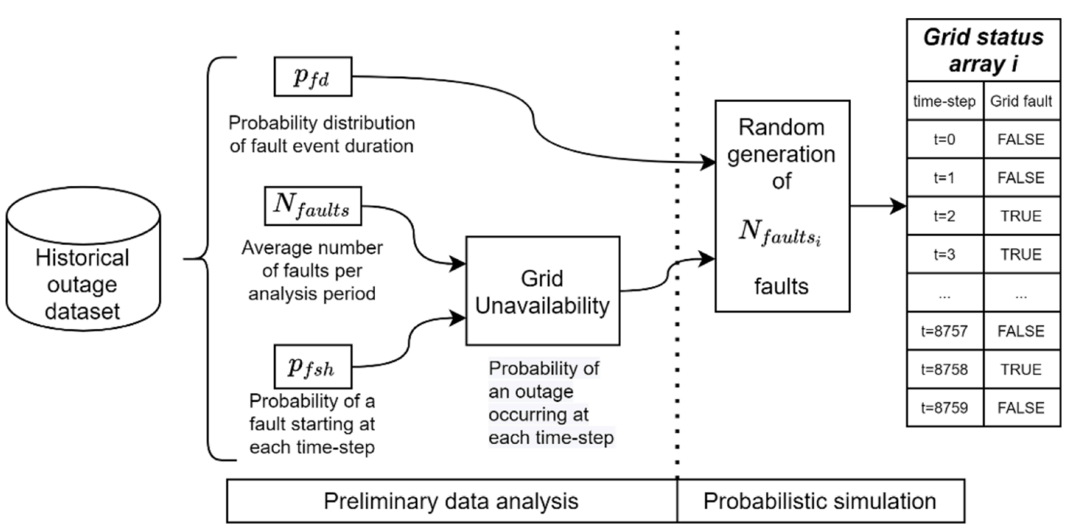

Figure 3. Creation of the grid status array with N_{faults_i} outage events from historical fault data.

period of one year.

A microgrid operation module was implemented to account for a microgrid as an alternative for reliability improvements. A microgrid with rooftop photovoltaic (PV) panels and a static battery energy storage system (BESS) is considered as a base, but the proposed modelling approach enables the inclusion of other energy resources, such as electric vehicles or small diesel generators. Figure 4 shows a simplified diagram of the microgrid operation module showing the outcome for the calculated total energy demand at each time-step of the microgrid simulation.

The microgrid operation module calculates the balance between demand, energy exchange with the distribution grid, local generation, and storage. The *grid status array* calculated as described in subsection 2.1.1 is used as an input to indicate the grid availability. A simple customer with no local energy resources can also be represented by the microgrid module by setting the energy resources' capacities on zero. This results in the customer being modelled as an array with the original energy demand data.

The customer demand from the grid when a microgrid is implemented is calculated as follows: at each time-step, the total microgrid energy demand for the grid connection, *gridreq*, is calculated considering the original customer demand *load*, the available generation *gen*, and the BESS state of charge. The customer is modelled as an array with 8760 values for the total energy demand for the grid. Local generation is considered as a negative load, and it reduces the amount of energy imported from the grid. Excess generation is exported to the grid or curtailed in time-steps when the grid is unavailable.

The BESS charging load B_c is considered as a positive load and added to the customer original demand when the BESS usable state of charge is below 100%, and either the grid or excess generation is available. BESS discharge B_{dc} is considered as a negative load. The BESS is discharged if the grid is unavailable and the local generation is not enough to meet the original customer demand.

The BESS is used only as grid back-up and detailed discussion on the microgrid operation module and the different possible operation strategies that can be implemented using BESS in different ways fall outside the scope of the paper.

The microgrid operation alters the experienced loss of electricity supply caused by grid faults. This introduces the need for defining the concept of perceived fault durations, the durations of outage events that in practice affect the individual customer after a microgrid with local energy resources has been implemented.

During grid outages, the microgrid relies only on the available local energy resources (PV system and BESS discharge) to meet the original customer demand. If the local generation is higher than the customer demand, the excess generation is used for charging the BESS or is curtailed, in case BESS is fully charged. During a grid fault, if the local resources are enough to meet the entire original demand during the complete fault duration, the fault is considered as avoided (not perceived) by the microgrid at that time-step. Therefore, the microgrid operation can be considered as a contingency measure for the event of the loss of the largest generating unit in the load-generation model.

When the local energy resources can meet just a fraction of the demand during a time step, but loss of load still occurs, the outage is

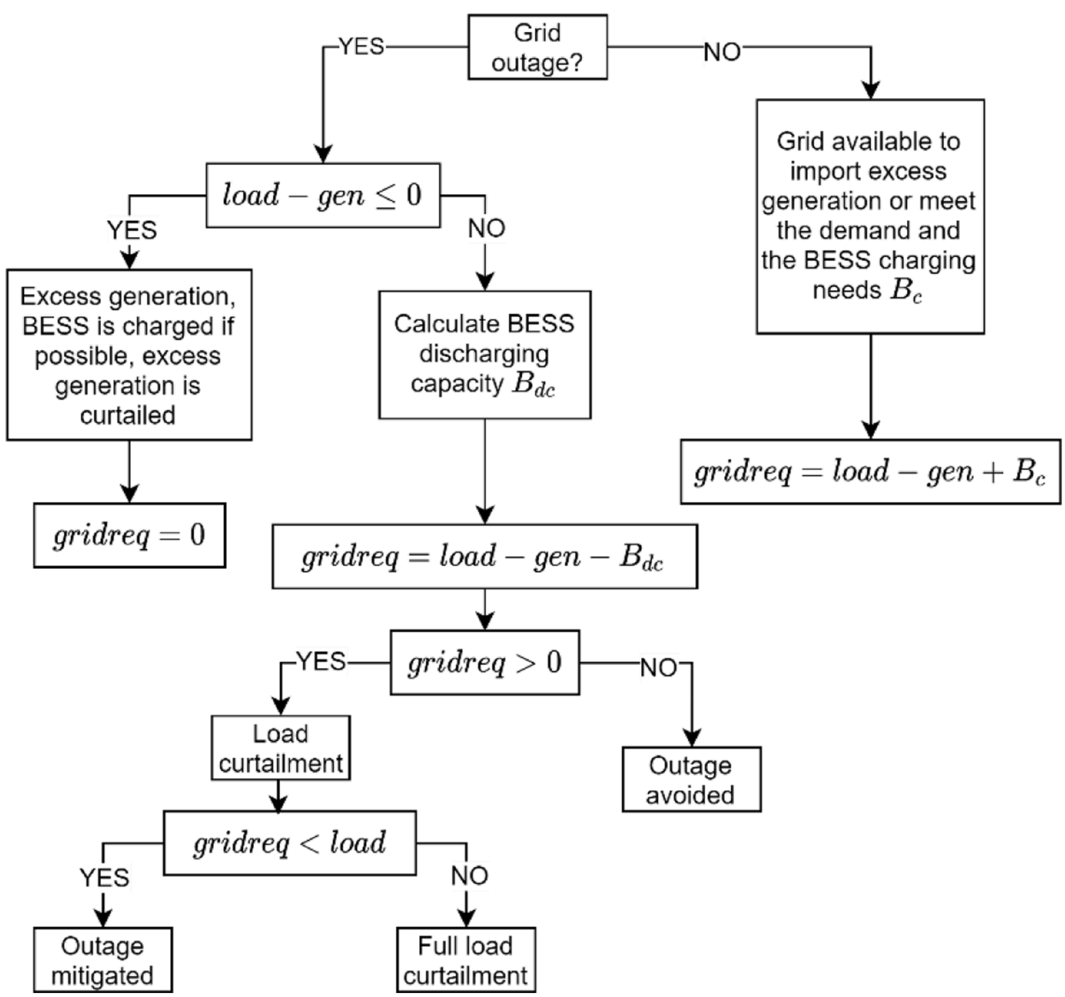

Figure 4. Simplified diagram of the microgrid module operation showing the grid requirements output for each time-step of the microgrid simulation.

mitigated but not avoided. With hourly time-steps, this means that the microgrid covers a portion of the energy demand for that hour, which makes the perceived duration of the outage smaller than the actual duration. When the BESS charge is depleted and there is no local generation, there is a total loss of load, and the fault is perceived as it occurs on the grid.

Calculated Reliability Indices

The proposed methodology aims at evaluating the reliability of electricity supply from a financial perspective for individual customers. This requires two critical information: (i) the amount of time that the electricity supply was lost for the customer, and (ii) the financial damages associated with this loss of supply. The following indices are defined and calculated to meet these requirements.

Expected Energy Not Served (EENS): The Expected Energy Not Served, also referred to as Expected Energy Not Supplied, gives the curtailed demand for a given period of time and is a classic index in power systems [14]. EENS is typically used in capacity adequacy studies for large power systems, and the evaluation of the expected loss of load is an important parameter for reliability [17]. In the proposed methodology, this index is calculated for an individual customer to express how much load is lost due to an interruption in electricity supply from the grid. Therefore, EENS provides an indication of how reliable the supply is.

Customer Outage Cost (CCOST): The Customer Outage Cost (CCOST) is an indication of financial damages (in €) incurred from a specific outage event. It is defined similarly as in [18] to evaluate the economic impacts from the loss of electricity supply in financial terms. Therefore, it must reflect the associated cost per outage duration with an estimation of how much load is not served during the outage event. The proposed CCOST combines the amount of energy not supplied (EENS), an indication of the supply reliability, with the Value of Lost Load (VoLL, sometimes referred to Customer Interruption Costs), which reflects how much each kWh of unserved energy costs [19]. This combination yields a purely financial value to indicate the damages incurred by each interruption of supply, expressing grid reliability as a monetary value. The combination of damages caused by all outage events in the analysis period, or a sum of all calculated CCOST, can then be used as a valuable input in the decision-making process for investments in reliability improvements.

A Customer Damage Function (CDF) is typical way of expressing, in terms of the lost load, the damage caused to a customer by a single interruption of electricity supply based on its duration and on the segment to which the customer belongs. Several surveys and research have been performed to define accurate CDFs for different sectors [20–24], but data regarding individual customers is limited. The calculation of CCOST is heavily dependent on a descriptive Customer Damage Function (CDF) for an individual customer. However, rather than expressing damages relative to lost load as a typical CDF, the Customer Outage Cost expresses the costs of loss of supply directly in financial terms.

The total financial damages caused by all faults that occur over a year is defined as $CCOST_{year}$. For a simulation over a period of one year and a *grid status array* with N_{faults_i},$CCOST_{year}$ is defined in Equation *1*.

$$CCOST_{year} = \sum_{k=0}^{N_{faults_i}} CIC_k \times L_{lost\,k} \quad (1)$$

Equation 1 $\boldsymbol{CCOST_{year}}$ calculation for a number N_{faults_i} of outage events over a year.

Where CIC_k is defined as the Customer Interruption Cost associated to fault k, obtained from a Customer Damage Function for the rural customer; and $L_{lost\,k}$is the amount of load lost (not supplied) during the outage event. Therefore, local energy resources installed behind-the-meter at an individual customer contribute to reducing the amount of load not supplied during and outage event, thus reducing the CCOST associated to that event.

The parameters CDF and CIC_k are heavily influenced by the availability and quality of data for a given customer or customer sector. Typically, Customer Interruption Cost (CIC), also defined as Value of Lost Load (VoLL), is expressed in either financial values per peak or average power [25] or per average or total energy consumption [23]. $L_{lost\,k}$ is thus given in then expressed in equivalent parameters for power or energy.

Probabilistic Method for Evaluating Individual Customer Reliability

The proposed load-generation unit pair model and the proposed reliability indices are highly dependent on the stochastic behaviour of grid outage events. Thus, a probabilistic method can be used for calculating the economic damages caused by grid faults.

A Monte Carlo simulation was implemented when calculating the economic value of grid reliability to an individual customer. Figure 5 shows the integration of the proposed modelling approach into the probabilistic method for calculating the model's reliability, and the following paragraphs explain in more detail the Monte Carlo sampling and the modelling process.

Each iteration of the Monte Carlo simulation performs three main operations: 1) sampling a new instance for the distribution grid as a generating unit as described in section 2.1.1; 2) the creation of the rural customer model as a load point through a microgrid simulation, described in section 2.1.2; and 3) the calculation of the relevant reliability indices for the load-generation unit pair, discussed in section 2.2.

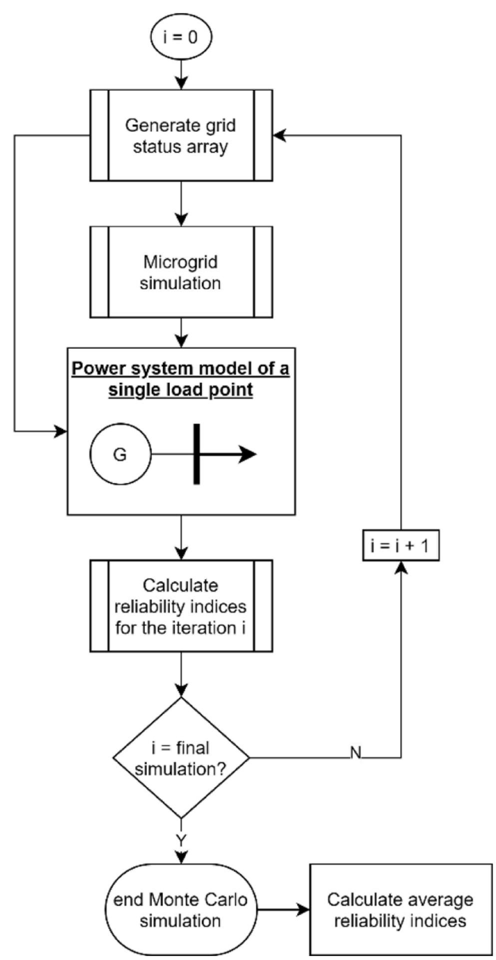

Figure 5. Monte Carlo simulation for the calculation of relevant reliability indices using the proposed load-generation unit pair model approach.

A unique *grid status array* is created in each iteration i of the Monte Carlo simulation, with a different number of faults N_{faults_i} and different fault durations. The number of iterations in the Monte Carlo simulation, $N_{iterations}$, must be sufficient for the average *grid status array* to provide a statistically significant representation of the availability of the grid connection for an individual customer. That is, the average number of faults $N_{faults_{sim}}$ over $N_{iterations}$ should converge to the average number of faults N_{faults} observed in the grid data to properly reflect the grid connection availability. The average reliability indices of EENS and $CCOST_{year}$ are calculated at the end of the Monte Carlo simulations for the number of simulations performed.

Comparison and benefits from the proposed methodology

Two aspects are considered in reliability studies: (i) the reliability indicators and their calculation methods; and (ii) the financial value associated to reliability of electricity supply. These aspects reflect how the reliability studies are often linked and serve as inputs to cost-benefit assessments for investments in grid infrastructure or added generation capacity.

Reliability indicators are typically associated with the grid infrastructure, and thus calculated accordingly. Indicators such as CAIFI and CAIDI, express consumer reliability through the calculated average for a distribution grid, rather than an individual reliability of supply for each customer. These individual aspects are particularly important in the context of rural consumers, a segment with great variation between consumer types, consumption range and requirements for steady supply of electricity.

The financial value of reliability is associated to a customer segment, and represented by a Customer Interruption Cost (CIC), often also referred to as the Value of Lost Load (VoLL) [19,26–28]. These indices express the financial value (in e.g. €/kWh) of the lost load, calculated through aggregated customer surveys and normalised by consumption ranges [29]. Some approaches assume just a single number for a customer segment, while in others CIC can depend on the duration and the timing of the event. Once more, the individuality of customers is neglected in such calculations.

The proposed methodology utilises individual consumer data to calculate reliability indices for specific consumers. It exploits the expanded digitalisation in the electricity sector that has produced a higher availability of individual consumption data to generate individual models for specific customers. Moreover, by building upon the concept of CIC and utilising customer-specific Customer Damage Functions, more accurate and representative damages can be calculated. The value of the load lost can be assessed for each individual customer, whereas the reliability of supply can be calculated considering a large number of potential outage events experienced by each customer. These results are then used to calculate the total financial damages caused by grid faults over an analysis period.

Similar analysis could also be made using Production Cost Models (PCM), even though they are typically used for large-scale studies. PCM performs an optimisation of costs of generation, dispatch, unit commitment, and loss of load to evaluate the cost-benefit for investments in grid infrastructure or additional generation capacity, including renewable energy [30–32]. The advantage of our method is a very low computational requirement, which allows for large samples in the Monte Carlo simulations and thus resulting in a more reliable estimate for the expected damage for customer types under different solutions to improve reliability. The limitation is that the method can be used only in relatively simple systems that can be represented by an algorithmic approach. The approach considers the diversity of situations where individual customers can find themselves in and gives appropriate weight to those circumstances. PCMs can then use this information to make more informed decisions between, e.g., a battery back-up and a grid connection upgrade either for individual customers or as part of larger energy system optimization. Alternatively, the proposed methodology can be used by individual customers, such as industrial customers and rural farms, to assess the cost-benefit of investing in local production and storage. This application is exemplified with a case study described in the following section.

CASE STUDY DESCRIPTION

A case study consisting of a grid-connected dairy farm in rural Finland is selected to demonstrate the proposed methodology and its flexibility. The dairy farm consumption and microgrid operations were modelled based on the discussion in [12] and utilises the same dataset for the load and solar power generation, obtained from [33].

Considering a rural customer in the case study is especially interesting, as these customers tend to suffer a higher number of disruptions, both long- and short-lasting [34]. Moreover, the investment costs for improving electricity supply reliability tend to be higher for rural areas, given a lower population density and longer distances between connection points.

Finland is a particularly relevant case when considering the Finnish Electricity Market Act [35] which establishes an obligation for Finnish distribution grid companies to improve the reliability of electricity supply, particularly in rural areas where the reliability is still below the one found in urban regions. These improvements are done typically by costly grid investments, such as underground cables, which again introduces the need for evaluating other cost-effective strategies.

The grid was modelled based on grid availability, obtained using a dataset of outage events that occurred at the Finnish electricity grid between 2015 and 2018. The outage event dataset was purchased from the Finnish company Enease, which assembled the data by collecting fault information from Finnish distribution system operators.

While the dataset consisted of over 260 thousand outage events, four years is not ideally representative in the context of grid faults, given their stochastic behaviour. A dataset consisting of a longer period would give a better indication of longer and rare outage events.

Scenario Description

Three scenarios are defined to demonstrate the methodology and its use for a rural customer in Finland when the reliability of electricity supply is improved by going from scenario I to either II or III:

I *Aerial:* Rural customer grid-connected via unprotected aerial cables

II *Underground:* Rural customer grid-connected with underground cables

III *Microgrid:* Rural customer as a microgrid, grid-connected via unprotected aerial cables.

Scenario I was defined as a benchmark case since it reflects the most common situation for customers in rural areas on Finland. In this case, electricity supply is typically from grid connections via unprotected aerial cables. Scenario II and Scenario III represent different options to improve reliability of electricity supply.

Scenario II consists of a rural customer grid-connected via underground cables, with the expected lower number of faults and different distributions of fault occurrences and durations.

Scenario III represents a rural microgrid with local energy resources (PV and BESS). This microgrid is still grid-connected and relies on the grid for most of its energy supply, but has islanding capabilities to mitigate the loss of supply during faults.

The $CCOST_{year}$ values calculated for each scenario can be compared against the needed investment costs for increasing grid reliability and the most cost-effective strategy for reducing customer damages from grid outages can be estimated.

Generator Model Based on Fault Historical Data

The generation unit in the proposed model is created using historical fault data for the electricity system in Finland. The original dataset contained over 260 thousand faults and was filtered to account only for outage events that are relevant to this study. This yielded a remaining dataset containing 177 thousand entries on unplanned interruptions that affected rural customers. The average fault duration for the full dataset was of 2.19 hours, with a minimum fault duration of 1 second and a maximum fault duration of 797.62 hours. Only 15 outage events in the full dataset lasted for more than 600 hours, and were thus considered as outliers, being removed from the analysis. Table 1 gives an overview of the dataset in terms of the number of faults considered in each simulated Scenario.

Figure 6 shows the calculated distributions for fault durations and fault starting hour (aggregated by month) for the complete fault dataset and for faults that affected aerial connections and underground cable connections. These distributions were used as fault duration probability (p_{fd}) in the creation of *grid status arrays* in the Monte Carlo simulation. Simplifications were assumed to ensure the created faults would properly reflect the dataset: faults that would start while another fault is still propagating through time were considered invalid, and no outage event would last longer than 600 hours (25 days) in the implemented simulations.

Rural Customer Model

A rural dairy farm was modelled using simulated data consisting of one year of hourly electricity demand given in kWh, considered at the connection point between the farm and the distribution network. The simulated data represented a typical consumption for a rural dairy farm in Finland for one year. Figure 7 shows the load profile for this simulated dairy farm during a week in Winter. The annual average demand for the rural dairy farm was 31.4 kWh per hour. The consumer is assumed to behave in the same way in emergency conditions as in under normal conditions, and no considerations on load prioritisation are made for the simulated dairy farm.

The microgrid components were also selected based on the study in [12] and implemented in the microgrid operation module for the simulations for the *Microgrid* scenario. Hourly solar power generation from [33] in per units was multiplied by the capacity of the PV array, set at 50 kWp.

The BESS capacity was defined so that the annualised investment costs for the *Microgrid* case would match the investment costs for the *Underground* case. Therefore, a capacity of 670 kWh was selected for the local BESS. This capacity would be enough to meet the demand for a full Summer day, and roughly 65% of the energy demand of a Winter day. The battery charge/discharge rates were defined from [12] and set as 100 kW. The purpose of the BESS was to act as a backup system during grid faults, as discussed earlier.

A grid-forming inverter was also considered in the *Microgrid* case to support the islanding operations during grid outages. The inverter rating was selected according to the maximum demand of the dairy farm and set at a capacity of 60 kW.

Table 1
Unplanned outages affecting rural customers dataset characteristics.

Unplanned interruptions that affected rural customers	177616
Interruptions affecting rural customers regardless of distribution type	108090
Aerial distribution	
Interruptions affecting only customers with aerial distribution	64618
Total number of faults affecting aerial distribution	172708
Average number of faults per year for aerial distribution	15.00
Underground distribution	
Interruptions affecting only customers with underground distribution	4909
Total number of faults affecting underground distribution	112999
Average number of faults per year for underground distribution	11.05

The effects of implementing a microgrid at the dairy farm are exemplified in Figure 8. A close-up on the dairy farm energy demand during a 73-hour outage event in March shows that the microgrid reduces the amount of lost load and the total duration of the perceived fault. When the grid connection is lost, the local energy resources are sufficient to meet the farm's demand for nearly the whole following day, effectively postponing the outage event by one day, thus reducing its duration.

Calculating CCOST and Defining a Customer Damage Function

Accurately defining the cost of reliability services is a challenge when considering the cost-benefit of investments for reliability improvements. The moment in time in which the loss of load occurs, and the duration of such event also play an important role in defining the price of reliability services. The financial damages caused by an interruption of electricity supply are often higher than just the price of the undelivered load. Therefore, the use of an accurate Customer Damage Function (CDF), one that is appropriate for the customer in question, is necessary to fully understand the financial damages caused by each interruption of electricity supply.

This paper uses a CDF derived from [36], which presents Customer Interruption Costs based on a survey with 163 farmhouses in Finland. This study yielded the CDF with CIC values in €/kW, obtained after normalising the estimated customer costs by the average seasonal peak power consumption of the rural farms over a year. Therefore, Equation 1 must be modified to adequately use the data available. Although the CDF was obtained from a survey using a representative customer group, it was conducted in 2013, and significant advancements in equipment connectivity have occurred in modernised farms since [37]. Therefore, rural farm customers may nowadays present a CDF closer to that of industry or retail, customer groups typically associated to great damages caused by short outage events [18].

Using the selected Customer Damage Function from [36] Equation 1 now can be expressed as:

$$CCOST_{year} = \sum_{k=0}^{N_{faults_i}} CIC_k \times P_{peak} \tag{2}$$

Equation 2 $\boldsymbol{CCOST_{year}}$ calculation for the dairy farm case with the selected CDF.

Where CIC_k is the Customer Interruption Cost for fault k given in €/kWh, and P_{peak} is the average peak power demand of the dairy farm over one year. The outcome is a sum of all the Customer Outage Cost incurred by each individual outage that occur over a year.

A linear interpolation is performed to generate the CDF shown in Figure 9, which highlights the CDF for outages that last between 1 minute and 4 hours to show that short-lasting outages do not yield significant financial damages for the dairy farm operation.

Two assumptions were made to calculate the CCOST for each fault: (i) after 96 hours of outage, the Customer Interruptions Costs continue to grow but at a reduced pace, considering that the majority of the financial damage is already done with the loss of dairy products; and (ii) a ceiling of 100 k€ as the maximum Customer Outage Cost for an individual outage event. These assumptions were considered to provide a realistic estimation of the financial damages of long-lasting outage events, which are not well represented in the used Customer Damage Function due to the rarity of their occurrence.

Costs of Improving Reliability Through Grid Investments or a Microgrid

A cost-benefit analysis of Scenarios II and III is performed by comparing their average $CCOST_{year}$ calculated from the Monte Carlo simulations and their needed investment costs against the benchmark Scenario I. These investment costs were estimated according to the

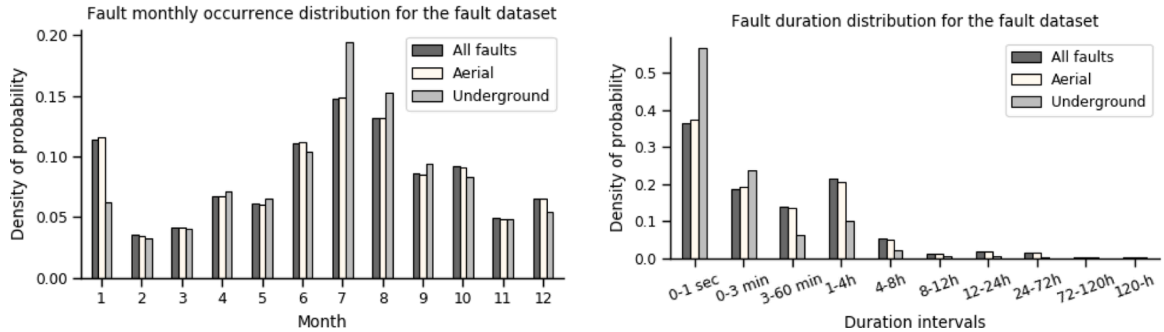

Figure 6. Distribution of faults in the outage dataset according to (a) fault duration and (b) fault starting hour, aggregated by month.

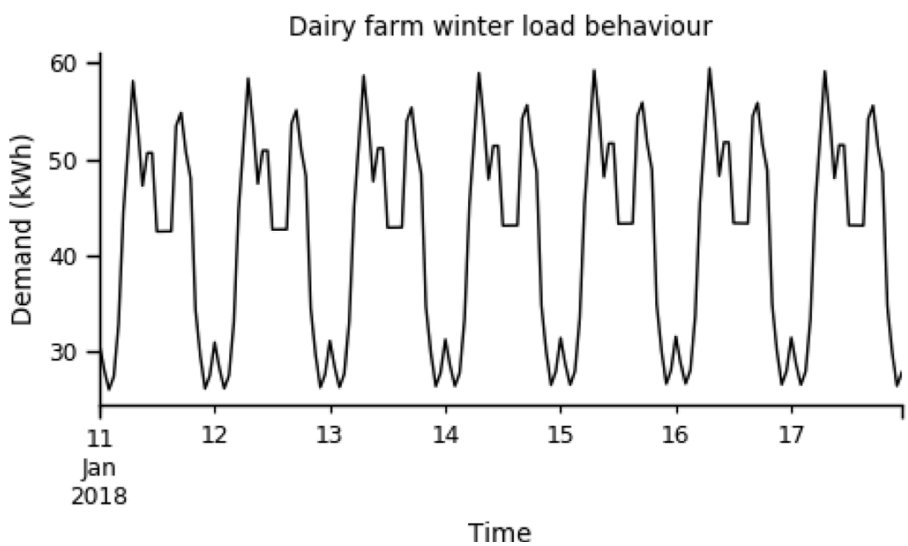

Figure 7. Energy demand profile for the modelled dairy farm during one week on Winter, showing the peak load demand.

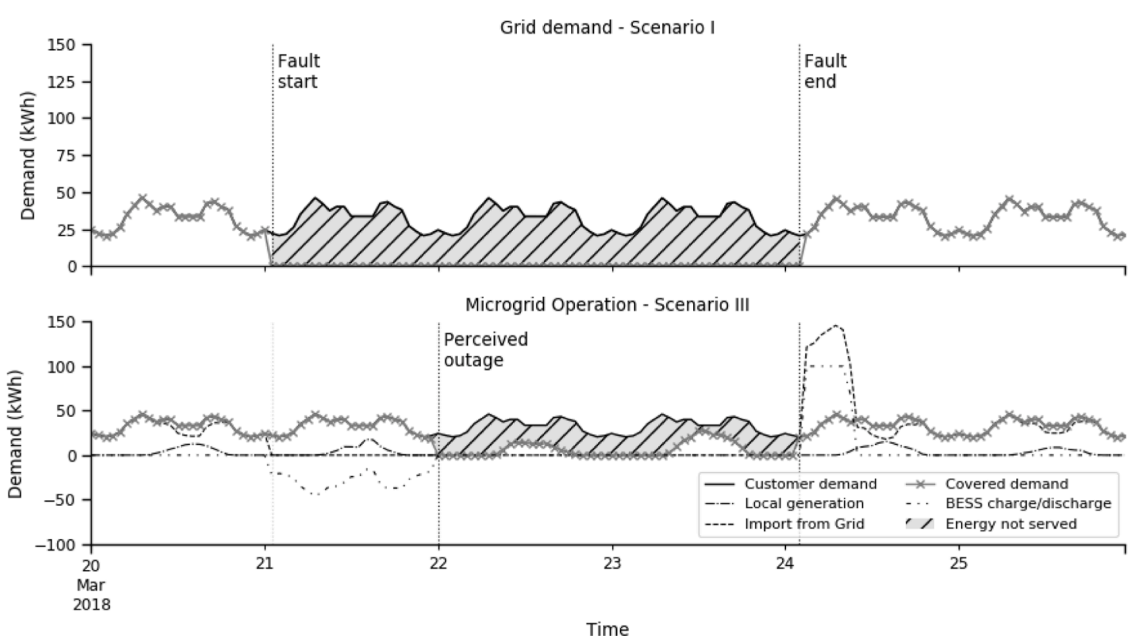

Figure 8. Dairy farm energy demand and energy not served for (a) a simple consumption case and (b) a microgrid with local PV generation and BESS.

discussion in [12], and updated to reflect values in 2020. PV array, local BESS and grid-forming inverter prices have been considered in approximate values to reflect retail prices based on recent market surveys [38,39]. All investment costs are considered without taxes, and maintenance and repair costs are not considered in this analysis. Comparing the financial damages caused by the loss of electricity supply

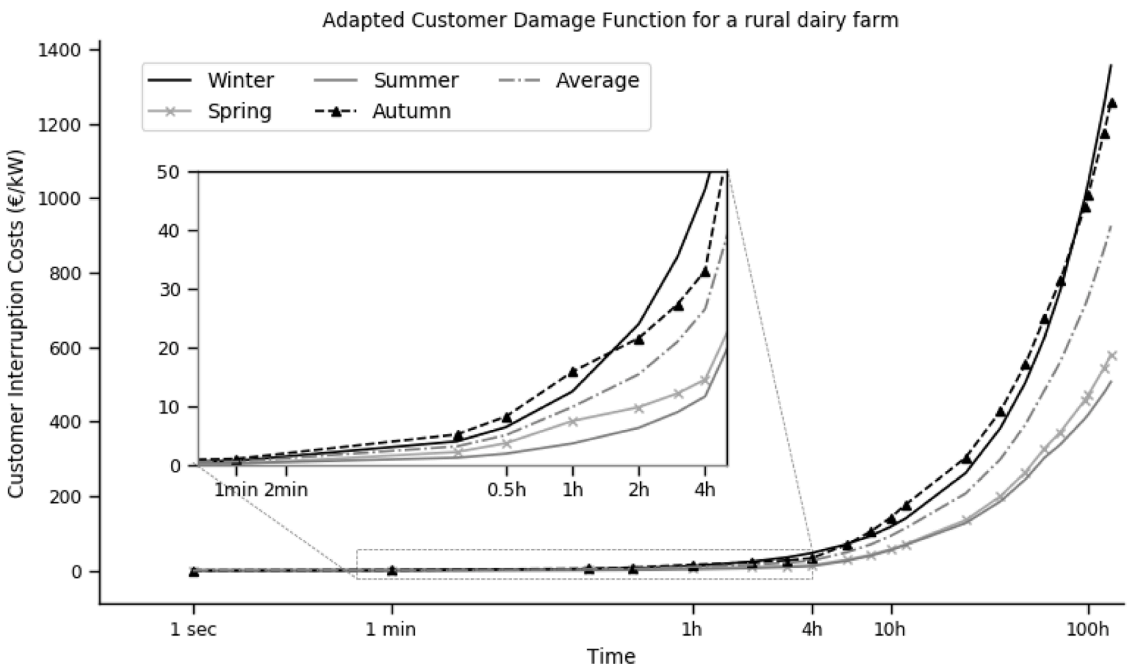

Figure 9. Customer Damage Function estimation for a rural dairy farm in Finland, adapted from [36].

($CCOST_{year}$) incurred in each scenario against their expected investments costs for reliability improvements enable the appropriate understanding of the financial worth of reliability services. Table 2 summarizes these values for the *Underground* and the *Microgrid* scenarios.

The annualized investment costs for Scenario II and for Scenario III are compared against the financial benefits to the customer. These benefits are yielded from the reduction in $CCOST_{year}$ that comes from an increased reliability of supply when compared to the benchmark Scenario I. The offset $Offset_{scenario}$ between the financial benefit and the investment costs is defined for each scenario according to Equation 3 and Equation 4:

$$Offset_{scII} = (CCOST_{scI} - CCOST_{scII}) - \frac{C_{price} \times C_{length}}{C_{lifetime}} \tag{3}$$

Equation 3 Offset calculation for the Underground scenario.

$$Offset_{scIII} = (CCOST_{scI} - CCOST_{scIII}) - \left(\frac{PV_{price}}{PV_{lifetime}} + \frac{BESS_{price}}{BESS_{lifetime}} + \frac{Inv_{price}}{Inv_{lifetime}}\right) \tag{4}$$

Equation 4 Offset calculation for the Microgrid scenario.

Table 2
Investment costs for Scenario II and Scenario III.

Scenario II: Underground cabling network	
Cabling length C_{length}	10 km
Cable price C_{price}	55000 €/km
Cable lifetime $C_{lifetime}$	40 years
Scenario III: Microgrid at the customer side	
PV array capacity	50 kWp
PV array price PV_{price}	40000 €, or 800 €/kWp
PV array lifetime $PV_{lifetime}$	30 years
BESS capacity	670 kWh (roughly one day consumption)
BESS price $BESS_{price}$	98000 €, or 140 €/kWh
BESS c-rate	100 kW charge and discharge
BESS lifetime $BESS_{lifetime}$	10 years
Grid-forming inverter capacity	60kW
Grid-forming inverter Inv_{price}	30000 €, or 500€/kW
Grid-forming inverter $Inv_{lifetime}$	10 years

Reliability improvements come at significant investment costs, either in grid infrastructure (Scenario II) or via the installation of local energy resources (Scenario III). These investments are seldom profitable from the perspective of the grid operator, but are motivated by grid regulation requiring an improved level of reliability in the electricity supply. Therefore, the offset is expected to be negative for all scenarios.

The proposed method analyses just the direct financial damages from the outages. Other financial aspects that influence the cost-benefit analysis from the DSO's and the customers' perspective were excluded in this first analysis. These financial aspects include customer compensations paid by the DSOs due to outages, or the potential customer income gained from exporting energy to the grid in the *Microgrid* case. These become increasingly important with a higher penetration of distributed energy resources in the grid and the associated regulatory changes. Thus the consideration of these financial aspects is proposed as future work.

RESULTS AND DISCUSSION

A Monte Carlo simulation was implemented for each Scenario. The average number of generated faults N_{faults} in the simulations reached statistical convergence to the values observed in the grid data after 3800 iterations. Therefore, $N_{iterations}$ was defined as 4000 to ensure an appropriate representation of the grid connection availability for the rural dairy farm.

Simulation Results: Modelling Accuracy and Reliability Indices

The accuracy of the generated faults in the Monte Carlo simulation was compared to the historical outage data. It was noted that the Monte Carlo simulation accurately represented the stochastic behaviour of the electricity grid outages extracted from the dataset. On average, 14.90 outage events were generated per iteration for the *Aerial* case (Scenario I), while 15.00 was the average in the dataset. For the *Underground* case, 10.99 outages were created on average while 11.05 was in the dataset. The numbers are slightly lower as some of the generated faults were considered invalid if they would occur during the propagation of a prior outage. Considering all generated faults (including the invalid faults), statistical convergence to the dataset was achieved.

Figure 10 shows a comparison between the fault distribution in the original dataset (hatched bars) and the generated faults for each Monte Carlo simulation. It shows that the proposed modelling strategy accurately represented the availability of the grid connection for a rural customer, properly reflecting the stochastic behaviour of grid outage events.

Outage events that affected the underground cabling network were less frequent and had a shorter duration, as was also observed in the historical data. Moreover, faults in the underground cabling network tend to occur at a higher frequency in the summer months in Finland, when the Customer Interruption Costs are typically lower for the selected use case. Faults affecting the aerial network happened at a much higher concentration during the winter months due to issues with crown snow load.

Table 3 shows the results from the Monte Carlo simulations for the *Aerial, Underground* and *Microgrid* cases. The average number of generated and perceived faults, as well as the average perceived fault durations, indicate that significant reliability improvements are yielded from both alternatives, with a decrease in the number of perceived faults, average EENS and a reduction on the average $CCOST_{year}$ for both Scenarios II (*Underground*) and III (*Microgrid*) when compared to the benchmark (*Aerial*).

With a microgrid, the customer could avoid nearly 99% of the simulated faults, which also led to a significant decrease in the calculated EENS (82.9%, or 793.66 kWh was avoided by the microgrid). Figure 11 shows that outage events up to 24 hours affected nearly no loss of electricity supply to the customer when a microgrid was in place. A microgrid with appropriate BESS and local generation capacity is able to ride through such faults without the need for load curtailment and with minor customer damages. Additionally, the microgrid also greatly reduced the average EENS for longer outage events. A microgrid was shown to be an effective way of diminishing the damages from grid outage events.

The calculated average $CCOST_{year}$ for each scenario expresses the financial damages caused by interruptions on electricity supply. The benchmark case presents an average CCOST of 11.4k€ per year for a rural dairy farm grid-connected through aerial cables. Investments in underground cabling could see these values decreasing significantly, with a reduction of yearly CCOSTS of 8.4k€. Alternatively, adopting a microgrid at the customer side would see the $CCOST_{year}$ reduced by 9.1k€ per year when compared to the benchmark.

Table 3
Simulated outage events for each scenario and associated perceived faults by the rural customer.

	Aerial	Underground	Microgrid
Average generated faults			
Number of simulated valid faults	14.89	10.99	14.92
Number of perceived faults	14.89	10.99	0.19
Perceived fault duration (hours)	2.17	0.88	32.17
Average reliability indices			
EENS (kWh)	997.94	284.22	163.66
$CCOST_{year}$(€)	11398.30	2961.05	2265.59
Cost of lost load (€/kWh)	11.42	10.42	13.84
Load covered by microgrid (kWh)	0	0	793.66

There is a clear improvement in the reliability of supply for the dairy farm in Scenarios II and III, demonstrated by the lower amount of EENS and lower $CCOST_{year}$. The calculated cost of lost load, or $CCOST_{year}$/EENS, indicates that in Scenario III more critical load is lost during the experienced outages, with an average value of 13.84 € per unserved kWh. This is justified by the rural customer only experiencing longer lasting faults when a microgrid was in place. The average fault duration of 32.17 hours indicates that the perceived faults for a microgrid would have higher Customer Interruption Costs and hence higher values for *CCOST*.

The longest outages (over 24 hours) cannot be avoided in the microgrid case due to solar PV being the only generation source. This means that many of the perceived outages are taking place during winter, when the Customer Interruption Costs are also typically higher for a rural dairy farm as shown in Figure 9. A small and reliable generator, such as a hydrogen fuel cell, could be an option to mitigate this and is proposed as a topic of further studies.

In addition to reducing the number and duration of perceived faults, a microgrid gives the customer time to react to the fault in order to plan which loads to curtail, unplug lower priority equipment, and to effectively reduce the Customer Interruption Costs associated with an outage event further than what was considered in this paper. The consideration of the introduced predictability of faults for a microgrid case is proposed as future work. To perform this, a new Customer Damage Function

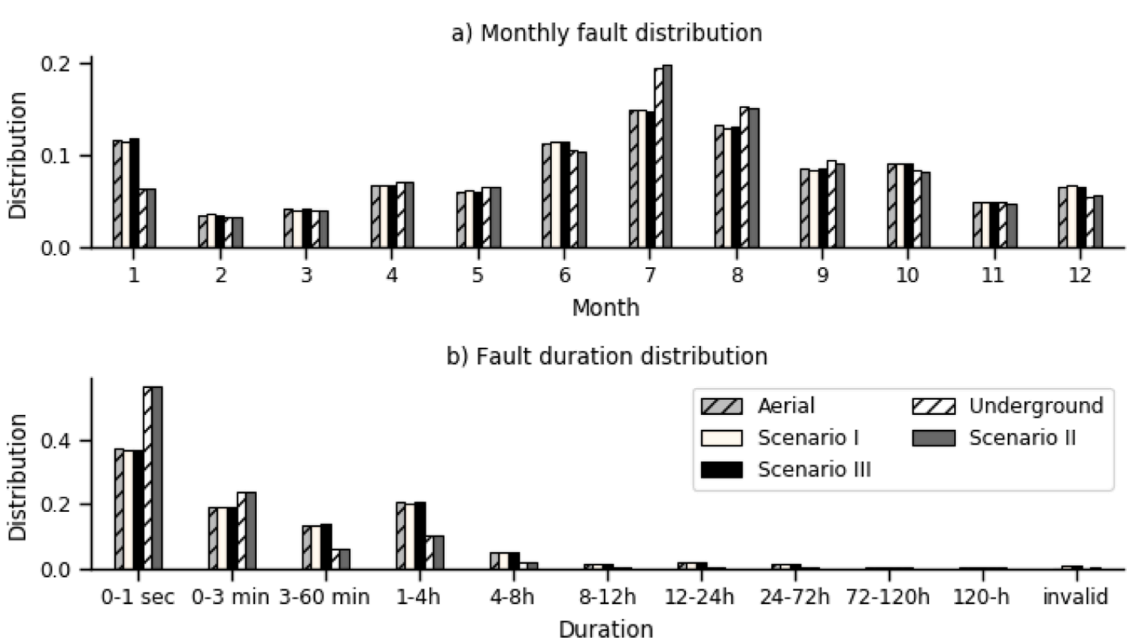

Figure 10. Distribution of (a) month in which faults occur and (b) time propagation of faults between the historic fault dataset (hatched bars) and the simulated scenarios, including invalid faults.

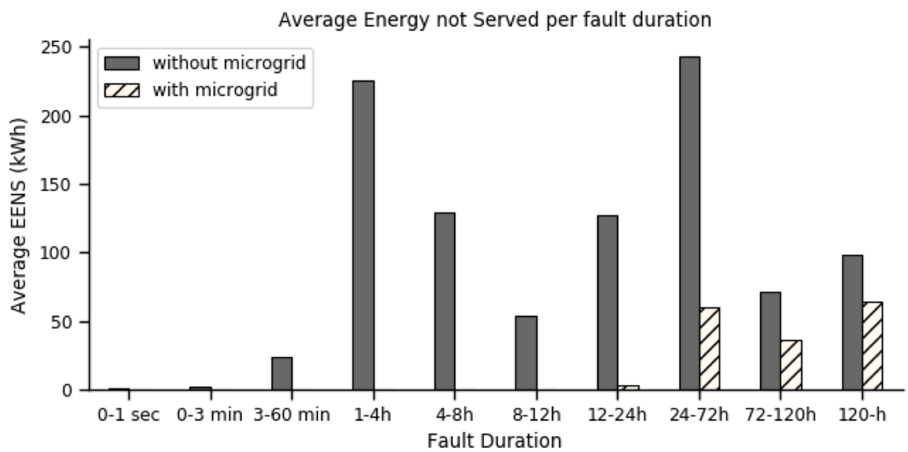

Figure 11. Average Expected Energy not Served for the generated faults (white) and for the perceived faults (hatched) in the Microgrid scenario.

should be estimated by asking individual customers what their estimated Customer Interruption Costs for a scenario with an implemented microgrid.

Cost-Benefit Analysis Results

Figure 12 shows the comparison between the necessary investment costs and the average $CCOST_{year}$ reduction for the *Underground* and the *Microgrid* scenarios. For the latter, investment costs are also separated into the three main components of the microgrid. The calculated Offset gives an indication on which case presents the highest increase in electricity supply reliability for the same annualised investment costs.

The annualised investment costs are alleviated by the reduction in the Customer Outage Costs, and the total expenses for increasing the reliability of a rural grid-connected customer via investments in underground cables would be approximately 5.3 k€ per year for the dairy farm case. Investments in a microgrid would yield total yearly costs of 4.7 k€. The financial cost of each kWh of avoided energy not served is calculated by dividing the Offset by the avoided EENS, yielding 7.44 €/kWh and 5.87 €/kWh for Scenarios II and III respectively. Therefore, the implemented microgrid presents lower investment costs for reducing the EENS for a rural customer. Table 4 shows this comparison.

Table 4
Financial benefit ($CCOST_{year}$ reduction) from the increased reliability yielded by investments in underground cabling (Scenario II) and a local microgrid (Scenario III) and financial value of each kWh of avoided lost load.

	Underground	Microgrid
Annualised Investment Costs (€/y)	-€ 13750.00	-€ 13713.3
$CCOST_{year}$ reduction (€/y)	€ 8437.25	€ 9051.35
Offset (€/y)	-€ 5312.75	-€ 4661.98
EENS reduction (kWh)	713.73	793.66
Cost of avoided loss of load (€/kWh)	7.44	5.87

Scenario III presented the highest reduction in yearly CCOST for a similar level of investments. It also yielded a greater reduction in the Expected Energy Not Served, which indicated a greater degree of availability of energy supply for the rural customer with a microgrid solution, as opposed to grid investments in underground cables. The total cost per kWh of avoided energy lost was also 1.6 €/kWh lower for the microgrid solution, indicating that this investment strategy yields greater reliability benefits for the same investment costs.

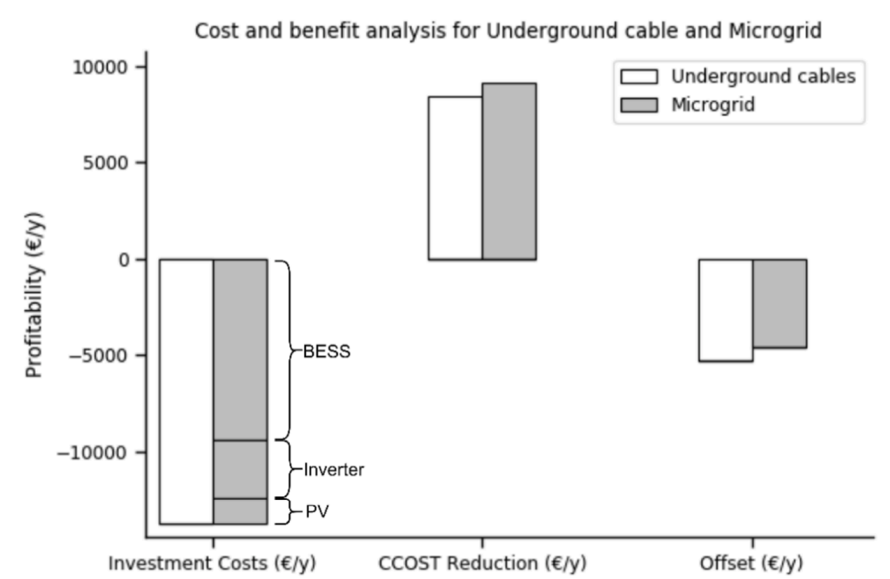

Figure 12. Profitability of increasing reliability of electricity supply through investments in underground cabling or microgrids. The investments for the Microgrid case are divided into the three main components considered in this analysis.

CONCLUSION AND FUTURE WORK

This paper proposes a simplified modelling approach for a rural customer and its grid connection. This simplified model is integrated in a probabilistic simulation, an approach typically used for large Power System capacity adequacy studies. This modelling strategy was shown to appropriately address the stochastic behaviour of grid outage events, accurately representing the availability of electricity supply through a grid connection for a rural customer based on historical outage data.

Furthermore, this paper also proposes an approach for calculating an individual consumer's reliability in terms of the financial damages incurred by the loss of electricity supply from the grid, calculated as the Customer Outage Costs (CCOST). The representation of reliability in economic terms enabled a proper comparison against investment costs for different alternatives for improving electricity supply reliability.

Both proposed approaches are demonstrated in a case study representing a dairy farm in Finland. The case study shows the flexibility and applicability of the proposed modelling strategy over three different scenarios, namely a benchmark case with the rural customer connected to the grid via aerial cables, via underground cables, and via aerial cables with the inclusion of local energy resources at the consumer side, forming a microgrid. A cost-benefit analysis is performed with the calculation of the CCOST for each scenario, demonstrating the applicability of the proposed method as an economic decision-making tool.

For the simulated scenarios, a microgrid yielded the highest reliability improvements per investment costs, with each kWh of avoided lost load costing 5.87 €. Comparatively, underground cabling yielded 7.44 € for each kWh of avoided lost load.

Although this paper discusses the flexibility of the proposed method and demonstrates a suitable application case for it, further studies must be performed to highlight its applicability in different sectors and customer profiles. Precise and reliable data on customer behaviour, existing connections and equipment, and Customer Interruption Costs is needed to fully demonstrate the potential of the proposed methodology for different cases. Future work is suggested on an approach to mitigate the requirements for precise parametric data.

Moreover, the consideration on the added predictability of grid outages and the respective decrease in Customer Interruption Costs for a microgrid case is also proposed as further improvements in the modelling strategy. The impacts of introducing local energy resources in the grid can also be analysed in the future. The proposed method can be expanded to consider individual customers' load prioritisation during outage events, further increasing the level of detail and reliability in the calculation of CCOST. Finally, a sensitivity analysis over the parameters of both the rural customer load, its Customer Damage Function, and the microgrid components is also proposed as future work.

CRediT authorship contribution statement

Sergio Motta: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Jari Ihonen:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Juha Kiviluoma:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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