Value of Lost Load: How much is supply security worth?

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***Abstract*—In the current operation of power systems, the paradigm states that the customer should be supplied with power at all times. The adherence to this paradigm may cause unnecessarily high costs. In order to operate a system where a supply-outage to customers is used as an acceptable, albeit expensive operative decision, it is essential to know the cost of this shedding. The classical method of calculating the Value of Lost Load (VOLL) has been the use of customer surveys. Due to their nature, surveys cover only a snapshot of the spectrum of parameters which affect the valuation. Moreover, VOLL is often expressed as a function of a single parameter such as duration of the outage or frequency of recurrence. This is inadequate modelling because a variety of parameters influence the magnitude of the costs incurred on account of an outage. The study in this paper presents an approach of using data from choice experiment surveys along with available interruption cost functions to introduce a more dynamic nature to the VOLL. Several parameters which affect the cost of an outage have been identified, classified and suitably incorporated into the model developed. The results from sensitivity analysis of the outage costs to these parameters show the possibility of using the concept of VOLL in short-term operative planning and contingency schemes of a power system, in addition to the more traditional use so far in long-term reliability planning.**

I. Introduction

Like all dynamic systems, electric power systems are at a risk of system failures. In order to restore the system to normal operating state after such a disturbance, measures such as load shedding may be taken, resulting in partial unavailability of supply. In such a case, a valuation of the loss of supply to the consumers versus the economic benefit to the system should be made and suitable measures such as compensating consumers should be taken to ensure fairness and balance between supplier and consumer [1]. Hence, the concept of Value of Lost Load (VOLL) arises, which is the value that consumers put on un-supplied electricity. VOLL is defined as the value an average customer puts on an un-supplied MWh of energy [2]. It is a measure of the loss that the customer suffers due to unavailability of electrical supply. It is normally expressed as different values for different types of consumers, which means that VOLL is defined separately for residential and commercial customers. VOLL can be an effective tool to estimate the total cost that arises due to an electrical outage. The study of VOLL is essentially the search for answers to the questions as formulated in [1]: “What is a consumer willing-to-pay to avoid an interruption?” and “What is a consumer willing-to-accept to agree for an interruption?”. It can thus be ascertained that an economically optimal reliability situation is achieved when the marginal costs of enhancing reliability equal the marginal benefits perceived by the consumers. For an electric supply system, while the marginal costs for increasing reliability could be estimated from the investments made by the system operator and their impact on the system performance, the task of estimating the marginal benefits perceived by consumers is much more difficult.

This study aims to provide an improvement over the current methods used to calculate the VOLL. An attempt to aggregate the results of several previous studies and of the various methods used to date is presented. Incorporation of several outage parameters and customer-side characteristics is intended to make the cost of an outage more specific to the particular circumstances, instead of having a single average value for all cases. A model is developed which employs specific parameters to differentiate between outages. Data from available customer damage function cost-bases are then used to estimate the cost of a specific outage. The model is tested by studying the impact of factors such as customer mix, dynamic load profile, time of the year and possible presence of advance warning on the total cost associated to an outage. This method allows cross-referencing different surveys to extract more information without the need for increasing question space or re-doing all the work; thus saving time, money and effort, whilst increasing usefulness.

The report is structured as follows: Section II provides a literature review discussing the existing methods used to estimate cost of outages followed by an analysis of pros and cons of each method, setting the stage for the need for an improved methodology. Section III provides a list of the various parameters identified from the previous studies, which significantly affect the cost of an outage. Section IV illustrates the methodology of the proposed model. Section V presents the results from the study while citing possible applications and scope for further research in this field.

II. Literature Review

Study of Outage Costs: History

Of the three different types of methods employed so far [4], customer surveys have emerged to be the most effective and hence, are most widely-used to estimate outage costs. These surveys incorporate a direct feedback from consumers and hence, are ideal for estimating the indirect costs related to an outage. However, conducting surveys is a challenging and cost-intensive task [4]. An important consideration is how to seek the desired information from the customers. The most direct approach is to provide customers with outage situations while asking them to assign an estimated value for costs they would incur due to it. Another approach is to ask customers either their willingness-to-pay to avoid a particular outage scenario or their willingness-to-accept compensation for a particular outage. However, on account of the non-conformity between these two valuations, results from such studies must be interpreted carefully [5], [7]. In an attempt at overcoming the limitations of direct surveys, indirect questions are employed to determine the cost of outages. One such method called preparatory action method involves asking consumers to select from a list of substitutes [8]. Another widely-used indirect method uses the conjoint analysis approach to obtain customer response to outage parameters [9]. Conjoint analysis or stated preference analysis is a statistical technique, with origins in behavioural modelling [10], involves *options* and *choices* between a number of hypothetical scenarios. The choices are not valued, but ranked.

Need for New Approach

A major limitation with most outage cost studies so far is that the duration of the outage and/or the frequency of recurrence are often regarded as the primary interruption-related variables. The results of the study are reported only as a function of this variable. This leads to a uni-dimensional treatment of the outage costs, which in reality, depends on several other parameters, as discussed in the following section. Another important factor is the non-inclusion of the load level of the system, i.e. the temporal variation of the consumption. This greatly affects the amount of lost load and hence, the Value of Lost Load (VOLL). Even though the load-factors and other interruption variables might be available, they are usually not reported, hence reducing the usefulness of published data. This study presents a new approach of using data from conjoint analysis along with available interruption cost functions to introduce a more dynamic nature to the calculation of VOLL.

III. Parameters: Identification and Classification

In addition to the duration of an interruption, several parameters, which differentiate one outage from another, have a considerable effect on the cost of a particular outage. The various parameters identified from previously published studies [1], [3], [6], [9] are characterized into three classes: outage or technical parameters, load-side or social parameters and other parameters.

Outage Parameters:

a) Duration of the Outage: For a commercial customer, even a momentary loss of power can cause huge costs of restarting the processes. For households, prolonged outages can cause discomfort, irritation and potential loss of recreational activities, while short duration outages might not.

b) Frequency of Recurrence: Increase in the frequency of outages may lead to increased dissatisfaction in the short term but to replacement strategies in the long run.

c) Time of the Day: While commercial customers would be most strongly affected by an outage during working hours, for the residential sector an outage during evening would be most unfavourable due to inconvenience and loss of recreation.

d) Day of the Week: Differences in energy usage pattern between the days of the week make this parameter significant.

e) Season of the Year: Seasonal differences in usage patterns involve the use of HVAC systems. Moreover, the geographical location of the region is a deciding factor.

f) Advance Warning: The presence of advance warning to the customers about the outage allows flexible customers to preferably shift their usage pattern.

Load-Side Parameters:

a) Customer Type and Size: Different types of consumers are affected differently by the same outage. In a very broad sense, customers may be divided into: residential and commercial sectors. This division is based upon the fact that households, unlike commercial customers don't use electricity to produce market goods.

b) Number of Customers: While each affected customer increases the outage costs, a few large customers affected may lead to higher costs than many small.

c) Energy Criticality: Most institutions such as hospitals with critical requirements for electricity have pre-installed backup supply systems. The cost of running backups and the time period for which it is available are crucial for deciding outage costs.

d) Degree of Substitutability: Refers to possible production steps in an industry where other energy sources like coal, oil or gas could replace electricity in short-term. For residential customers, an example would be using gas stoves for cooking rather than electric pans.

Other Parameters: In addition to the parameters described above, which can be modelled conveniently, there exist certain factors which affect the cost of an outage but can not be modelled effectively. Cultural and economic differences often lead to different levels of service quality to be labelled as "reliable". This subjectiveness of the perceived cost of outages can neither be mathematically modelled nor can be effectively captured in the responses to customer surveys.

IV. Modeling

The model proposed is termed as the "β - γ Model" where the β-coefficient is an indicator of the outage parameters (signifying the relative rank of an outage), while the γ-coefficient is decided by the load-side parameters. From the complete set of parameters which characterize an outage, suitable parameters (β and γ-coefficients) have been extracted. In addition to these parameters, other identified parameters exist, grouped as δ, which have not been considered in this modelling due to unavailability of appropriate data. These δ parameters include parameters discussed in the Section III such as frequency of recurrence of the outage, the energy criticality of the loads and degree of substitutability of electric supply.

A. β-Coefficient: Outage Parameters

The β-coefficient is a combination of parameters of an outage, which differentiates between various outage scenarios and ranks them in order of their severity. A more severe outage implies higher total cost associated with it. The parameters which constitute the β-coefficient in the model are defined as:

Season of the year, SEA $\in \{$*Summer,Autumn,Winter,Spring*$\}$

Day of Week, DOW $\in \{$*Weekday,Weekend,Weekday-Holiday*$\}$

Time of Day, TOD $\in \{$*Morning,Afternoon,Evening,Night*$\}$

Presence of advance warning, ADV $\in \{$*Yes,No*$\}$

The hours of the day are split as in [9]. The outage duration has been considered separately because it is assumed that an increase in duration has a similar effect on cost for all the outage scenarios. Moreover, the scope of the study is limited to single instances of outage and hence the parameter frequency of recurrence of outage is not considered as well. The above mentioned components of β relate to the time of occurrence of the outage (in terms of seasonality, weekend-weekday variation and intra-day variations) and whether there is an advance warning.

To obtain the relative ranking between outages, the results from a conjoint analysis survey, as discussed in Section II, commissioned by the *Dutch Office of Energy Regulation* [9] is used in this study. The parameters, which constitute the β-coefficient discussed above, were varied in the questionnaire in such a way that the change in cost valuation of an outage by the customers in response to variation in one or more parameters could be quantified. The study in [9] presents the results of this survey in the form of a table of dummy variables, which could be attributed as cost elasticities of the outage with respect to the chosen parameters. Hence, relative variations in these parameters bring about the changes in the severity of an outage and indirectly impact the cost of the outage. Finally, the β-coefficient of an outage is given by Equation (1), where ϵ_{i}'s are the dummy variables for season, day of the week, time of day and advance warning, respectively as obtained from [9].

$$\beta_{\text{outage}} = \epsilon_{\text{SEA}} + \epsilon_{\text{DOW}} + \epsilon_{\text{TOD}} + \epsilon_{\text{ADV}} \tag{1}$$

B. γ-Coefficient: Load-Side Parameters

The γ-coefficient is a measure of load-side characteristics of an outage and indicates the magnitude of the outage impact. To evaluate the γ-coefficient, the customers are first classified into residential and commercial sectors. This segregation is significant because consumers in these sectors have different uses for energy, distinct magnitudes and occurrence times of peak demand and in most cases, are geographically segregated. With regards to the pattern of energy usage, the peak demand for commercial customers lies during the day because of the working hours while the same occurs during evening hours for residential customers. This, along with the weekend-weekday difference for these sectors, leads to different cost valuation, thus necessitating sector-wise modelling.

As a second step, the percentage of each type of consumers considered is obtained. This data along with the sector-wise peak demand and daily load profile for these sectors is typically available to the electric supply utilities on account of the different tariff structures followed. Due to unavailability of suitable data and for reasons of simplicity, these values were assumed to be 10 kW for residential sector and 100 kW for commercial consumers, taking into account the average size of customers in these sectors. This is an assumption and use of real peak demand data if available, should improve the accuracy of modelling.

$$\gamma_{\text{res}} = N_{\text{res}} \times \text{HLF}_{res} \times \text{PD}_{res} \tag{2}$$

$$\gamma_{\text{com}} = N_{\text{com}} \times \text{HLF}_{com} \times \text{PD}_{com} \tag{3}$$

The equations (2), (3) provide the hourly values of γ-coefficient, where N_{i} and PD_i are the total number of customers and daily peak demand in each sector. HLF_i corresponds to sector-wise daily load factors in hourly intervals and is normalized to daily peak demand, lying in the range of [0,1]: 1 corresponding to the hour with peak demand, while 0 to hours with no demand or an outage. The data for calculating the load factor in this model was obtained from load data available from the public utility of the city of San Diego, California [11]. The sector-wise load factor for the i th hour of the day is determined by equation (4).

$$\text{SLF}_i = \frac{\text{Sector demand in hour } i \text{ (kW)}}{\text{Sector daily peak demand (kW)}} \tag{4}$$

C. Cost-Bases or Customer Damage Functions(CDFs)

From surveys undertaken in the past, Customer Damage Function (CDF), which gives the average interruption cost per customer as a function of outage duration, can be obtained for each sector of customers. Although CDF provides an important measure to quantify outage cost, as discussed previously, its usage is limited by the averaging effect of the entire year and considering all outages as being equal. CDFs are usually expressed in terms of monetary unit (MU) per kW of peak power demand or per kWh of peak energy demand. This model considers the CDFs obtained from an american study from 1987 [4], a finnish study from 1999 [2] and a swiss study from 2002 [12], because they adopt a similar classification of customers.

D. Data Pre-Processing

To solve the issue of currency differences and time change in monetary worth, suitable time discounting and historical currency conversion needs to be performed. This converts the CDFs into a common currency expressed at a reference point in time.

Further issues include that the studies [4], [2] and [12] provide only discrete point mapping of CDFs with respect to outage duration. These cost bases are suitably interpolated/extrapolated using piecewise linear interpolation, based on the assumption that the dependency is generally smooth.

E. Calculating Modified Cost Curves

The β-coefficient of an outage can be modified by the addition of a logarithmic function of outage duration to obtain Proxy Cost, PC, given by equation (5).

$$\mathrm{PC} = \beta_{\text{outage}} + \kappa_{\mathrm{D}} \times \log(t_D) \tag{5}$$

The logarithmic modelling of the effect of outage duration, t_D, is equivalent to the assumption that the disutility, and hence associated cost due to an outage, increases at a slower rate than its duration [9]. It is supported by a psychological theory known as Weber-Fechner's Law [13]. The coefficient κ_{D} ($\kappa_{\mathrm{D,res}} = -0.39; \kappa_{\mathrm{D,com}} = -0.27$) [9] is the dummy variable for the outage cost elasticity with respect to duration. The determination of PC is followed by anchoring it to the cost-base curves (interpolated CDF curves). The mean of all the proxy costs from various possible values of β-coefficients must be scaled to match the cost-base curves as given by equations (6)-(7), where k[Monetary units/kW] is the scaling factor obtained by dividing the discrete CDF values with mean β.

$$\text{Cost-base curve} = k \times (\text{Mean Proxy Cost}) \tag{6}$$

$$k = \frac{\mathrm{CDF}_{D_i}}{\beta_{\text{mean}}} \tag{7}$$

Similar k values obtained at all durations D_i allow the translation of average deviations of β values of outages to the CDF curves to obtain modified cost. For an outage scenario described by β_{o} with a duration $\mathrm{D_o}$ and β_{mean}, β_{max} and β_{min} being mean, maximum and minimum of all β values, the average deviation is defined as:

$$\sigma_{\beta_{\mathrm{o}}} = \frac{\beta_{\mathrm{o}} - \beta_{\text{mean}}}{\beta_{\text{max}} - \beta_{\text{min}}} \tag{8}$$

$$(\mathrm{MC})_{\mathrm{D_o}} = |(\mathrm{CDF})_{\mathrm{D_o}} \times \sigma_{\beta_{\mathrm{o}}}| \tag{9}$$

The modified cost (MC) curves transform the static CDFs, making them dynamic and outage specific depending on relative severity. When sector-wise modified cost curve is multiplied to the net load lost in each sector (given by γ), the total outage cost due to customers in each sector can be obtained and the sum of total costs from both these sectors: residential, $\mathrm{CC_{res}}$ and commercial, $\mathrm{CC_{com}}$, gives the net Value of Lost Load.

$$\text{Outage Cost} = \mathrm{CC_{res}} + \mathrm{CC_{com}} \tag{10}$$

For the American and Swiss studies, where CDFs are expressed in terms of CHF per kW of peak demand:

$$\mathrm{CC_{res}} = \gamma_{\text{res}} \times (\mathrm{MC})_{\text{res}} \tag{11}$$

$$\mathrm{CC_{com}} = \gamma_{\text{com}} \times (\mathrm{MC})_{\text{com}} \tag{12}$$

Whereas for the finnish study results, where CDF is expressed in terms of CHF per kWh of energy not served:

$$\mathrm{CC_{res}} = \underbrace{(\gamma_{\text{res}} \times \text{Duration(in hours)})}_{\text{Energy Not Supplied}} \times (\mathrm{MC})_{\text{res}} \tag{13}$$

$$\mathrm{CC_{com}} = \underbrace{(\gamma_{\text{com}} \times \text{Duration(in hours)})}_{\text{Energy Not Supplied}} \times (\mathrm{MC})_{\text{com}} \tag{14}$$

The subscripts 'res' and 'com' refer to residential and commercial customer sectors respectively. Figure 1 outlines the method schematically.

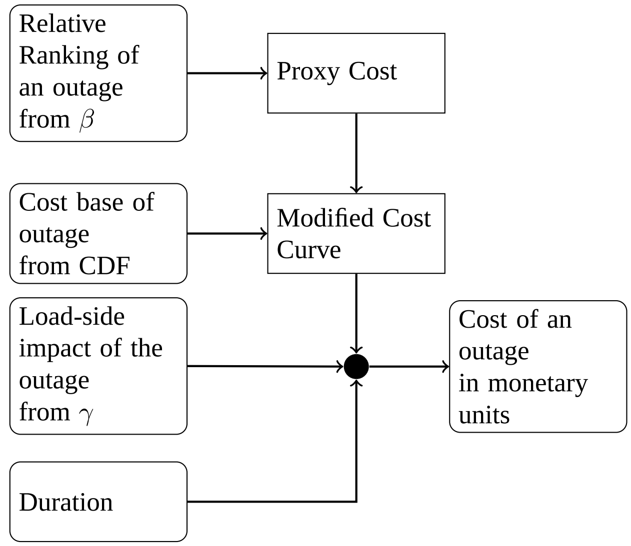

Fig. 1. Schematic for calculation of the outage costs

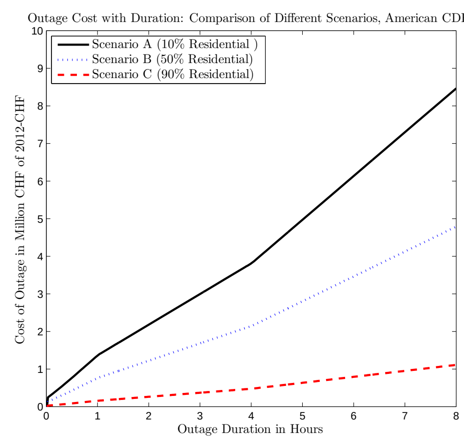

Fig. 2. Comparison of outage costs for the different Scenarios A, B and C

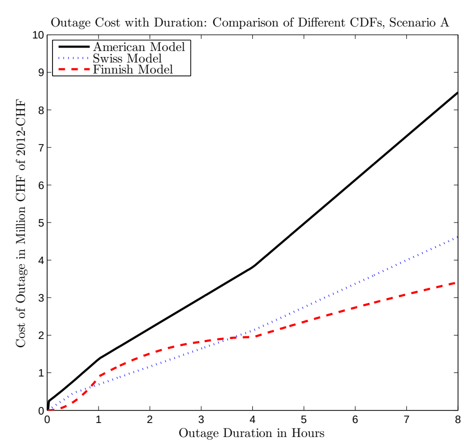

Fig. 3. Comparison of outage costs for the various CDF studies: American, Swiss and Finnish

V. Results and Conclusion

The case of a small town with an assumed total of 10000 customers has been considered, while different customer mix scenarios are framed (A: 10% , B: 50% and C: 90% of all customers assumed to belong to residential sector). A study of the sensitivity of outage cost to various outage parameters and to the three different Customer Damage Functions (CDFs) is performed in this case. The magnitude of cost values indicate that the cost of an outage is several times higher than the actual price of load un-supplied because electricity as a primary source of energy leads to production of goods and services, which also include leisure activities, valued at a much higher price. The sensitivity analysis conducted on the model shows that the presence of advance warning leads to a lower cost for the outages and that both the sectors of customers respond similarly to this parameter. Seasonality of outage costs is much significant for residential sector because commercial activities are largely non-seasonal while household energy needs are closely correlated to weather patterns. For scenario A (10% residential), an outage on a weekday afternoon can be as high as 10 times that for a region with mix similar to scenario C. Figure 2, showing a comparison between the scenarios, demonstrates the huge impact which the parameter of customer size has on the costs perceived due to an outage. Figure 3 shows the contrast in costs obtained from the three different surveys chosen and it portrays the disparity between them and supports the fact that survey results can not be translated from one geographical region to another without any modification. The difference in behaviour of the finnish outage cost can be attributed to the unsymmetrical and skewed CDF data and the fact that this study expresses CDF as a function of energy not supplied (in kWh) in contrast to the other two studies where CDFs were expressed in terms of peak demand (in kW).

Applications of the Model: The outage-specific calculation of Value of Lost Load (VOLL) allows its possible application in operation planning of power systems: power plant maintenance outages scheduling, forced load shedding and contingency response in a manner to reduce the net economic costs on account of loss of supply. In addition, the model can aid the process of long-term reliability investment decisions. The direct extension of this model is to incorporate the case of recurring outages. The islanded operation of growing distributed generation systems at the load-side can be taken into account as they can support the power system during contingencies and should be compensated accordingly. Moreover, changes in conventional load profile due to upcoming concentrated loads such as electric vehicles should be taken into account. The cost of the inconvenience caused by being unable to charge one's electric car due to an absence of electric supply could be a new concept altogether, possibly alleviated by the battery's storage capacity.

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