# CUSTOMER OUTAGE COST MODELS - COMPARISON

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## *ABSTRACT*

*Since new regulatory frameworks have been implemented, the distribution utilities have become more business oriented. Accordingly, they need to resolve and balance economic and reliability concerns by means of incorporating both reliability criteria and cost considerations in their decision-making process. In the past, the majority of utilities based their selection of a reliability criterion on experience and judgment of the planning engineers. Moreover, they did not explicitly incorporate customer cost consideration in their analysis. The determination of what is an acceptable level of reliability should recognize the perceived impacts seen by customers. These impacts can be considered in the form of Customer Outage Cost Model, which provides valuable information to balancing the economic and reliability aspects. Since the Customer Outage Cost Model used in the assessment of the reliability worth might directly influence on the decision-making process, this paper evaluates three different customer outage cost models. Namely, these are: Aggregated or Average Cost Model, Probabilistic Cost Model, and Fuzzy Cost Model. By means of numerical examples, the practical features of the three models are revealed. Finally, the result analysis and conclusions are presented.*

## INTRODUCTION

Since new regulatory frameworks have been implemented, the distribution utility ***(DU)*** has become more business oriented. Accordingly, it needs to resolve and balance economic and reliability concerns by means of incorporating both reliability criteria and cost considerations in their decision-making process. Before the changes in the regulatory laws took place, most of the ***DUs*** did not directly deal with the aspects related to the distribution system reliability.

Even more, the ***DUs*** did not explicitly incorporate customer cost consideration in their analysis. Nowadays, an acceptable level of reliability is compared with arbitrary criteria which are only inadequate for neither validating the suggested capital investments, but also portraying the actual customer impacts as a result of system interruptions [2, 6, and 9]. Then, the determination of what is an acceptable level of reliability should recognize the perceived impacts seen by the customers.

The monetary costs, which result from the evaluation of these impacts, have become a key indicator of the reliability worth [2, 6, and 9]. The reliability worth is assessed by means of the Customer Outage Cost ***(COC)***. The ***COC*** has been represented by different models, such as: Aggregated or Average Cost Model ***(AACM)***, Probabilistic Cost Model ***(PCM)***, and Fuzzy Cost Model ***(FCM)***.

This paper attempts to evaluate the reliability worth applying these different cost models by means of numerical examples in order to reveal their practical characteristics and make comparison regarding the decision-making process.

The content of this paper is structured as follows: a brief description of the reliability worth is given in the second section. In the third section, a broad description of the assessed customer cost model is presented. Next, the description of the distribution system data and the considered cases are showed. Subsequently, the obtained results are reported. Finally, the conclusions are exposed in the last section.

## RELIABILITY WORTH

Broadly speaking, performing the reliability worth analysis requires an assessment of the cost of providing reliable service, Reliability Cost, and a quantification of the worth of having it, Reliability Worth [8].

In general, the direct assessment of the reliability worth has been recognized as a difficult task because of there are many intangibles aspects involved in the evaluation process, which are not always possible to quantify in monetary terms [4].

A practical alternative, which is being utilized, is to evaluate the impacts and the customer monetary losses due to an outage by means of customer surveys [2, 6, and 9]. The customer survey are based on the assumption that customers are in the best position to understand how interruptions affect them [3, 8, and 9].

## CUSTOMER OUTAGE COST MODEL

After analyzing the collected data by the surveys, it is possible to create functions or models of interruption cost depending on the interruption duration for any particular customer or sector of customers. This function is known as Customer Damage Function ***(CDF)*** and can be determined for a given customer type and aggregated to produce Sector Customer Damage Function ***(SCDF)***. The ***SCDF*** can be combined to create a Composite Customer Damage Function ***(CCDF)*** [2].

In this paper, ***SCDF*** and ***CCDF***, i. e. the customer outage costs, have been implemented from three different approaches, which are aggregated or average, probabilistic, and fuzzy approach.

## Aggregated or Average Cost Model (AACM)

Customers are asked to provide their best estimates of monetary losses for selected outage scenarios [3, 8]. Thus, the survey provides data which can be conveniently used to create either ***CDFs*** or ***SCDFs*** for specific customer classes and sectors, or ***CCDF*** for a complete service area or distribution system ***(DisS)***. The ***AACM*** for a particular duration can be calculated in several forms such as: average cost per interruption, aggregated consumption-normalized cost, aggregated peak load-normalized cost, and average peak-normalized cost. The equation (1) shows the latter form, which is used in this paper.

$$\text{AvPNC} = \frac{\sum_{i=1}^{m} \dfrac{\text{cost}_i}{\text{peakLoad}_i}}{m} \quad \left(\textit{monetary unit / kW}\right) \qquad (1)$$

Where AvPNC is average peak load-normalized cost, $i$ is *ith* respondent, $\text{cost}_i$ is cost estimated in monetary units of *ith* respondent, $\text{peakLoad}_i$ is annual peak load in kW of the *ith* respondent, and $m$ is the number of respondents for which usable cost estimates and peak load values are available. Table 1 shows the obtained ***AACM***. The ***AACM*** for the sector Ind-Res, which refers to the composite Industrial-Residential customer sector in Table 1, is a direct result of the development of the corresponding ***CCDF***.

**Table 1 – AACM for the Considered Sectors**

| Sector | Interruption Duration (hrs) - Cost ($/kW) | | | |
|---|---|---|---|---|
| | **0.33** | **1** | **4** | **8** |
| Industrial | 16.4323 | 26.3094 | 63.0637 | 101.8375 |
| Residential | 0.023 | 0.1428 | 1.8849 | 4.4545 |
| Ind-Res | 10.4832 | 16.8229 | 40.8838 | 66.5320 |

## Probabilistic Cost Model (PCM)

In order to develop a ***PCM***, every customer response must be in one of the following forms: cost per interruption, consumption-normalized cost, or peak load-normalized cost. Particularly in this paper, the peak load-normalized cost form was used.

Briefly speaking, the principal idea that is applied to develop a ***PCM*** is to transform the entire cost data set from a surveyed specific duration into other data set, which is represented by a normal probability distribution using the normality transformation [4, 8]. Therefore, the inherent dispersion of the customer responses is handled in this way and incorporated within the ***COC*** model, and therefore the reliability worth assessment.

The normality transformation equations are:

$$y = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \log(x) & \text{if } \lambda = 0 \end{cases} \qquad (2)$$

Where $x$ is the original cost, $\lambda$ is the normality power transformation exponent, and $y$ is the transformed cost. To convert to the corresponding actual customer cost $x$, the inverse function of the equation (2) is applied.

The normality transformation has two limitations which are as follows. It applies only to continuous variables, and it does not apply to zero-valued data. In accordance to [4, 8], to fulfill these constraints, zero-valued customer outage cost are extracted and treated separately. The remaining data are analyzed using an iterative procedure that determines the value of $\lambda$ which best transform the data set into a normal probability distribution. The reference [8] describes comprehensively this procedure.

The ***PCM*** for specific customer sector and outage duration is defined by four unique parameters: normality power transformation exponent $\boldsymbol{\lambda}$, the proportion of zero-valued data ***Pz***, the characteristic parameters of the normal probability distribution; mean $\boldsymbol{\mu}$, and variance $\boldsymbol{\sigma^2}$. Table 2 shows the parameters that characterize the ***PCM*** for the industrial, residential sector [4].

**Table 2 – PCM Parameters for the Considered Customer Sectors**

| Duration (Hrs) | Sector | λ | μ | $\sigma^2$ | Pz |
|---|---|---|---|---|---|
| 0.33 | Industrial | -0.6605 | 1.0487 | 2.7866 | 0.1513 |
| | Residential | -0.2207 | -5.6618 | 4.8689 | 0.3295 |
| | Ind-Res | -0.2239 | 0.1027 | 2.0802 | 0.4011 |
| 1 | Industrial | -0.0707 | 1.6327 | 2.3443 | 0.0613 |
| | Residential | -0.1828 | -2.7329 | 2.8790 | 0.0973 |
| | Ind-Res | -0.0703 | 1.2478 | 2.2240 | 0.1476 |
| 4 | Industrial | -0.0387 | 2.8272 | 2.3620 | 0.0047 |
| | Residential | -0.0105 | 0.2886 | 1.6551 | 0.0265 |
| | Ind-Res | -0.0483 | 2.4234 | 1.6900 | 0.0311 |
| 8 | Industrial | -0.0020 | 3.6939 | 2.9880 | 0.0047 |
| | Residential | -0.0160 | 1.1345 | 1.5725 | 0.0426 |
| | Ind-Res | -0.0159 | 3.1742 | 1.7967 | 0.0470 |

Moreover, Table 2 presents the ***PCM*** parameters of the Ind-Res sector, which refers to the composite Industrial-Residential sector. These parameters were originally obtained in this paper. As can be noted, cost data are not available for all possible outage durations since the number of interruption scenarios which can be used in a survey questionnaire is limited. In order to describe the interruption costs at non-surveyed outage durations, regression analysis is used to estimate the four parameters. Thus, these equations between the studied duration values and each of the four parameters are obtained using the least-square method. Therefore, a particular parameter at a non-surveyed duration can be predicted by substituting the outage duration value into the respective equation.

## Fuzzy Cost Model (FCM)

Only the results based on mean values may not be a good representation for the reliability worth analysis in view of that the customer perception regarding the outage cost for a given scenario can differ considerably different from one another [3, 7, and 8]. To cope with this kind of uncertainty, the fuzzy arithmetic and logic can be suitably applied in order to develop a Fuzzy Cost Model [7]. The ***FCM***

provides a fuzzy representation for the entire customer cost data at each one of the surveyed outage durations. Nevertheless, this fuzzy representation can be achieved in different ways. For instance, the shape of the fuzzy representation may be obtained by means a fuzzy inference system. In this paper, the customer cost data are represented by means of a trapezoidal fuzzy number which has been obtained applying a procedure similar to that in [7].
Any trapezoidal fuzzy number can be represented by four parameters, ***a*, *b*, *c***, and ***d***, which correspond to its vertices. The selection of this fuzzy representation obeys the intention of achieving the reliability worth without applying the extension principle to compute the fuzzy arithmetic operations. It is recognized that the extension principle is computationally demanding. For that reason, the function principle is an effective way of performing fuzzy arithmetic operations with lower computational burden [5, 10]. Subsequently, Table 3 presents the ***FCM*** in the form of trapezoid parameters for every considered customer sector, where $\mu(a) = \mu(d) = 0$ and $\mu(b) = \mu(c) = 1$.

**Table 3 – FCM for the Considered Customer Sectors**

| Duration (Hrs) | Sector | *a* | *b* | *c* | *d* |
|---|---|---|---|---|---|
| 20/60 | Industrial | 0 | 0.0379 | 0.1842 | 492.1 |
| | Residential | 0 | 0.00135 | 0.00311 | 0.0886 |
| | Ind-Res | 0 | 0.0286 | 0.1294 | 313.50 |
| 1 | Industrial | 0 | 0.0189 | 0.0557 | 340.2 |
| | Residential | 0 | 0.00452 | 0.00672 | 0.3542 |
| | Ind-Res | 0 | 0.0428 | 0.0937 | 220.00 |
| 4 | Industrial | 0 | 0.0519 | 0.0654 | 173.0 |
| | Residential | 0 | 0.01546 | 0.02221 | 2.1000 |
| | Ind-Res | 0 | 0.2055 | 0.6508 | 113.60 |
| 8 | Industrial | 0 | 0.0206 | 0.0206 | 103.5 |
| | Residential | 0 | 0.08549 | 0.85490 | 3.0200 |
| | Ind-Res | 0 | 0.9260 | 0.9260 | 68.65 |

## DISTRIBUTION SYSTEM DATA

The distribution system RBTS Bus 2 [1], shown in Figure 1, was employed to illustrate the application of the three aforementioned Customer Outage Models. This distribution system is composed of four radial feeders and twenty two load points. Moreover, it is assumed that the distribution system is balanced. The feeder type and length data are included in [1]. Meanwhile, the customer composition and loading data of the distribution system are shown in Table 4 and Table 5 respectively. From Table 4 and Table 5, the applied load peak composition for the Feeder 4 is 63.7% and 36.3% of industrial and residential load respectively. Additionally, the reliability data assumed for the 11kV distribution system components is shown in Table 6, where $\lambda$, *r*, and *st* are average failure rate, average repair time, and average switching time respectively.

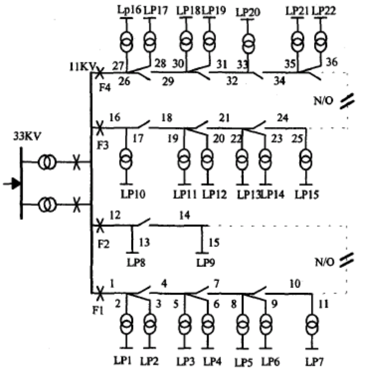

**Figure 1 - Distribution System – RBTS Bus 2**

**Table 4 - Customer Composition for Every Load Point**

| Load Points | Type | Load - MW Average | Load - MW Peak | Number of Customers |
|---|---|---|---|---|
| LP1 - LP7, LP10,LP11 | Residential | 0.535 | 0.8668 | 210 |
| LP12-LP19 | Residential | 0.450 | 0.7291 | 200 |
| LP8, LP20, LP21 | Industrial | 1.000 | 1.6279 | 1 |
| LP9, LP22 | Industrial | 1.150 | 1.8721 | 1 |

**Table 5 - Loading Data of the Distribution System**

| Feeder Number | Load Points | Feeder Load MW Average | Feeder Load MW Peak | Number of Customers |
|---|---|---|---|---|
| F1 | LP1 - LP7 | 3.745 | 6.068 | 1470 |
| F2 | LP8 - LP9 | 2.150 | 3.500 | 2 |
| F3 | LP10 - LP15 | 2.870 | 4.650 | 1220 |
| F4 | LP16 - LP22 | 4.950 | 8.044 | 803 |
| Total - Distribution System | | 13.715 | 22.262 | 3495 |

**Table 6 - Reliability Data**

| Component | λ (f/yr.km) | r (hrs) | st (hrs) |
|---|---|---|---|
| Transformer 11/0.45 kV | 0.015 | 10 | 1 |
| Lines | 0.065 | 5 | 1 |

## CONSIDERED CASES

The three customer outage cost models were used to carry out the reliability worth assessment of the ***DisS*** shown in Figure 1. The results of such assessment are presented in form of feeder indexes such as Expected Outages Cost ***(ECOST)*** and Interrupted Energy Assessment Rate ***(IEAR)***. The evaluated cases are as follows:
**Case 1**: The only protection equipment present in the distribution system is the breaker at the beginning of each feeder. Every single failure anywhere in the feeder makes the corresponding breaker operate. **Case 2**: This case considers in addition to Case 1 installing fuses in every lateral branch. Therefore, twenty two fuses are installed in the ***DisS***. **Case 3**: This case considers in addition to Case 1 installing disconnect switches in selected locations in the

main sections of each feeder. Therefore, ten disconnect switches are installed in the ***DisS***.
As general assumptions, it has that the studies only consider the 11kV feeders and ignore any failure in the 33kV system. Furthermore, it assumes that all the 11kV protection equipments operate successfully when required.

## RESULT ANALYSIS

In order to apply and compare the three ***COC*** models in the reliability worth assessment, the following general considerations were made. The ***PCM*** parameters for the industrial and residential sectors in Table 2 were employed to artificially construct the customer cost data set required to obtain the remaining ***COC*** models. This task was accomplished by means of Monte Carlo Simulations which were required to fulfill the following criteria: confidence level $\alpha = 10\%$ and maximum convergence error MaxError = 5%. The resulting ***AACM*** for every considered customer sector was obtained through the equation (1) and is presented in the Table 1. Moreover, the ***PCM*** parameters for the composite Industrial-Residential sector were obtained applying the procedure exposed in [8] and they are reported in Table 2. Then, the ***FCMs*** corresponding to every considered customer sector were computed and they are presented in Table 3.
The reliability worth assessment was tackled depending on the ***COC*** model in different manners. Namely: (1) Considering the ***AACM***, the analytical assessment of the reliability worth was applied. (2) On the other hand, sequential Monte Carlo simulations ***(SMCS)*** were conducted to evaluate the reliability worth considering the ***PCM***. The ***SMCS*** was required to meet the criteria of $\alpha$ = 10% and MaxError = 7.5%. (3) Lastly, Considering the ***FCM***, the analytical assessment of the reliability worth was used. Now, the results of the reliability worth assessment are presented.
It found that the ***ECOST*** and ***IEAR*** values, which are reported in Table 7 and Table 8 respectively, are different between the ***AACM*** and ***PCM*** cases.
These differences basically fall on the ***COC*** models. For instance, F1 and F3 which are compounded only by residential customer, have ***PCM-ECOST*** and ***PCM-IEAR*** values higher than the corresponding ***AACM-ECOST*** and ***AACM-IEAR*** ones.
Conversely, F2 and F4 which have industrial customers, show ***PCM-ECOST*** and ***PCM-IEAR*** values lower than the corresponding ***AACM-ECOST*** and ***AACM-IEAR*** ones. In these cases, it can infer that using the ***AACM***, which does not considered the variation of the cost data, might overvalue the ***ECOST*** and ***IEAR*** in F1 and F3.
On the other hand, analyzing the ***IEAR*** values for a specific feeder and ***COC*** model, it can realize that this indicator is scarcely disturbed by the protection philosophy. Thus, ***IEAR*** would only depend on the customer type and ***DisS*** topology.

**Table 7 - ECOST Given by AACM and PCM**

| Feeder | Approach | ECOST (k$/yr) Case 1 | ECOST (k$/yr) Case 2 | ECOST (k$/yr) Case 3 |
|---|---|---|---|---|
| F1 | AACM | 7.099 | **2.492** | 4.505 |
| | PCM | 8.534 | **3.368** | 6.614 |
| **F2** | AACM | 30.336 | **22.109** | 26.034 |
| | PCM | 20.919 | **15.207** | 18.251 |
| F3 | AACM | 4.822 | **1.923** | 3.087 |
| | PCM | 5.988 | **2.583** | 3.984 |
| **F4** | AACM | 164.340 | **62.039** | 134.060 |
| | PCM | 106.894 | **43.629** | 93.249 |

**Table 8 – IEAR Given by AACM and PCM**

| Feeder | Approach | IEAR ($/kWh) Case 1 | IEAR ($/kWh) Case 2 | IEAR ($/kWh) Case 3 |
|---|---|---|---|---|
| F1 | Analytical | 0.519 | 0.506 | 0.483 |
| | SMCS | 0.660 | 0.692 | 0.699 |
| **F2** | Analytical | 14.717 | 14.717 | 15.338 |
| | SMCS | 10.344 | 10.394 | 11.656 |
| F3 | Analytical | 0.519 | 0.506 | 0.483 |
| | SMCS | 0.682 | 0.711 | 0.657 |
| **F4** | Analytical | 9.096 | 9.382 | 9.554 |
| | SMCS | 6.084 | 6.638 | 6.477 |

Moreover, it can observe in Figure 2 that the ***IEAR*** cumulative probability functions, which were obtained for every case by the ***SMCS***, are quite similar. That reinforces the fact that the ***IEAR*** hardly depend on the protection philosophy of the feeders.

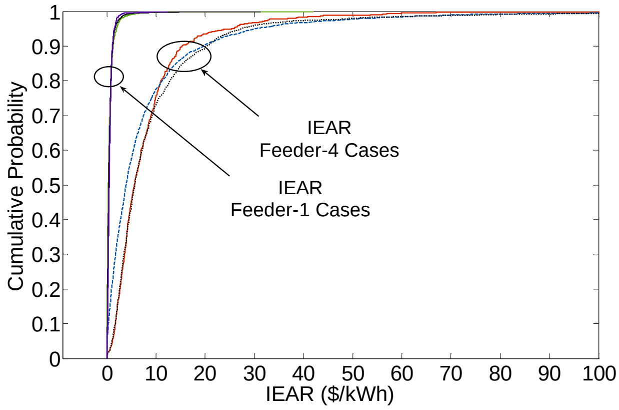


**Figure 2 – Cumulative Probability IEAR – Feeder1 and Feeder 4**

Whereas, Figure 3 depicts that the ***ECOST*** are highly dependent of the protection philosophy used in the feeders since the cumulative probability curves for F1 and F4 cases are really different between each other. Regarding the ***FCM***, Table 9 and Table 10 show the results of the reliability worth assessment which are trapezoidal fuzzy numbers. Comparing ***ECOST*** and ***IEAR*** given by the ***AACM*** and ***PCM*** (Table 7 and Table 8) to the corresponding fuzzy results given by the ***FCM*** (Table 9 and Table 10), some interesting results show up.

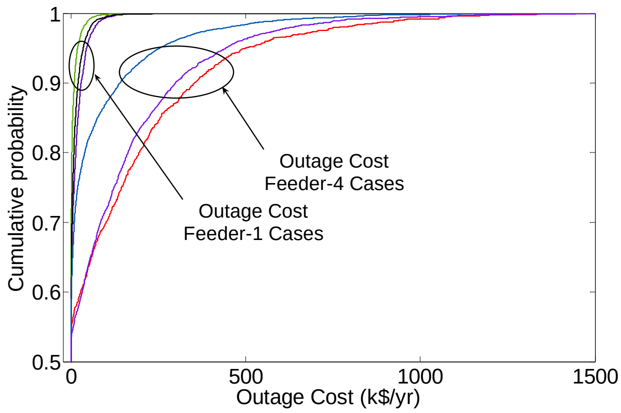


**Figure 3 - Cumulative Probability ECOST – Feeder 1 and Feeder 4**

**Table 9 – Expected Cost Given by FCM**

| Feeder | Case | ECOST(k$/yr) | | | | Fuzzy Mean |
|---|---|---|---|---|---|---|
| | | *a* | *b* | *c* | *d* | (k$/yr) |
| F1 | Case 1 | 0 | 0.100 | 0.640 | 5.965 | 2.353 |
| | **Case 2** | **0** | **0.030** | **0.134** | **2.256** | **0.867** |
| | Case 3 | 0 | 0.066 | 0.408 | 3.986 | 1.568 |
| F2 | Case 1 | 0 | 0.016 | 0.019 | 60.450 | 22.534 |
| | **Case 2** | **0** | **0.012** | **0.014** | **44.057** | **16.423** |
| | Case 3 | 0 | 0.014 | 0.020 | 78.065 | 29.098 |
| F3 | Case 1 | 0 | 0.067 | 0.425 | 4.069 | 1.603 |
| | **Case 2** | **0** | **0.023** | **0.103** | **1.741** | **0.669** |
| | Case 3 | 0 | 0.044 | 0.268 | 2.747 | 1.078 |
| F4 | Case 1 | 0 | 1.527 | 2.429 | 272.636 | 102.200 |
| | **Case 2** | **0** | **0.487** | **0.935** | **116.840** | **43.757** |
| | Case 3 | 0 | 1.153 | 1.852 | 382.815 | 143.120 |

**Table 10 – IEAR Given by FCM**

| Feeder | Case | IEAR($/kWh) | | | | Fuzzy Mean |
|---|---|---|---|---|---|---|
| | | *a* | *b* | *c* | *d* | ($/kWh) |
| F1 | Case 1 | 0 | 0.007 | 0.047 | 0.436 | 0.172 |
| | Case 2 | 0 | 0.006 | 0.027 | 0.458 | 0.176 |
| | Case 3 | 0 | 0.007 | 0.044 | 0.428 | 0.168 |
| F2 | Case 1 | 0 | 0.008 | 0.009 | 29.326 | 10.932 |
| | Case 2 | 0 | 0.008 | 0.009 | 29.326 | 10.932 |
| | Case 3 | 0 | 0.008 | 0.012 | 45.994 | 17.144 |
| F3 | Case 1 | 0 | 0.007 | 0.046 | 0.438 | 0.173 |
| | Case 2 | 0 | 0.006 | 0.027 | 0.458 | 0.176 |
| | Case 3 | 0 | 0.007 | 0.042 | 0.430 | 0.169 |
| F4 | Case 1 | 0 | 0.085 | 0.134 | 15.090 | 5.657 |
| | Case 2 | 0 | 0.074 | 0.141 | 17.669 | 6.617 |
| | Case 3 | 0 | 0.082 | 0.132 | 27.282 | 10.199 |

For instance, feeders only with residential customers, F1 and F3, reported ***AACM-PCM ECOST*** and ***IEAR*** higher than the respective ***d*** parameters. Namely, this means that the former values are outside of the support set of the corresponding fuzzy numbers, i.e. interval ***[a, d]***. Equally interesting is that for feeders with some industrial load component, such as F2 and F4, the ***AACM-PCM ECOST*** and ***IEAR*** are contained within the support set of the respective fuzzy numbers, i.e. interval ***[a, d]***.

The aforementioned suggests that for F1 and F3 the ***ECOST*** and ***IEAR*** might result an overvaluation if the reliability worth is carried out with the ***AACM*** or ***PCM***. Meanwhile, ***ECOST*** and ***IEAR*** of F2 and F4 would be suitable indicators since they are within the support set of the respective fuzzy number. Figure 4 shows the fuzzy ***IEAR*** for F2. It can observe that ***IEAR*** for Case 1 and Case 2 are exactly the same (Table 10). However, the fuzzy Case 3 ***IEAR*** is different in the vertex ***d***. This is mainly ascribable to the log-log interpolation applied to obtain the ***FCM*** in non-surveyed outage durations. This effect was more remarkable in the F2 and F4 Cases than in the F1 and F3 Cases. As can see in Figure 5, the tree fuzzy numbers are very close to each other. These results suggest that ***IEAR*** is very stable despite the ***COC*** model that had been used.

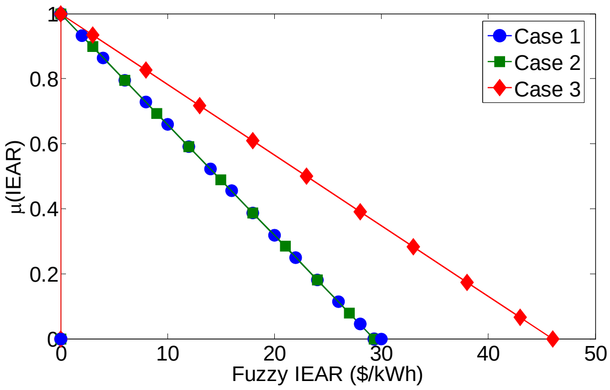


**Figure 4 – Fuzzy IEAR for Feeder 2 Cases**

Finally, Table 9 and Table 10 report in the seventh column the result of calculating the Fuzzy Mean. This was accomplished in order to make comparison among the obtained fuzzy numbers [10]. Broadly speaking, computing the fuzzy means implies the application of the Mellin Transform, which is deeply described in [10] and it is out of scope of this paper.

The fuzzy means calculation is not computationally demanding and is very convenient to carry out comparison and ranking operations in presence of uncertainty which has been modeled by means of trapezoidal or triangular fuzzy numbers.

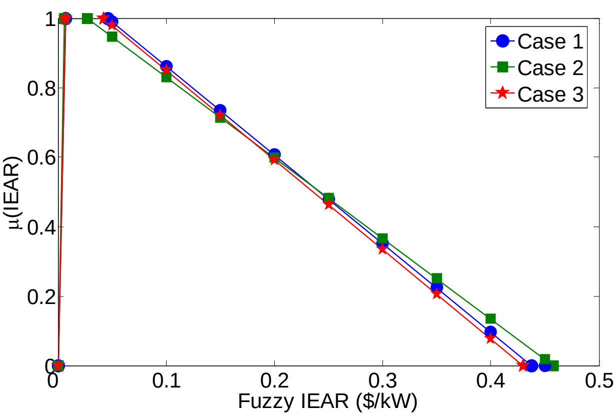


**Figure 5 – Fuzzy IEAR for Feeder 3 Cases**

## CONCLUSIONS

In this paper three different ***COC*** models have been used to carry out the reliability worth assessment in a ***DisS***. The ***AACM***, ***PCM***, and ***FCM***, in distinct ways, incorporate the customer perception regarding the ***DisS*** reliability into the reliability worth assessment. ***AACM*** used in this paper is based on average value of the customer cost data for specific outage duration. Being its more remarkable weakness the disregard for the natural variability of the actual customer cost data. To cope with that, ***PCM*** provides a structured framework to handle the uncertainty in the customer cost data by means of normal probability distributions. Because of that, ***PCM*** is more complicated than ***AACM***. Moreover, to use the ***PCM*** in reliability worth assessment, Monte Carlo Simulations are indispensable. Therefore, the required computational effort might become a drawback and it is also likely that slow convergence problems occur. On the other hand, ***FCM*** implicitly takes into account the bias and the skewness of the entire data set for particular outage duration. Accordingly, ***FCM*** captures and portrays these characteristics by means of trapezoidal fuzzy numbers. The determination of the fuzzy representation is an open question and could be biased to another fuzzy representation. However, the reported approach deals with the data bias and skewness, which are really incorporated within the final ***FCM***.

Unlike what happens with ***PCM***, ***FCM*** can be perfectly used with an analytical reliability assessment what becomes very attractive since the computational efficiency and lower computing time are guaranteed. Meanwhile, the results provide with enough evidence to confirm that ***IEAR*** is very stable regardless ***COC*** model applied and the protection philosophy used in radial ***DisS***. Therefore, ***IEAR*** shows suitable characteristics to be considered as the monetary value or price of the energy not-supplied.

Moreover, the ***ECOST*** results portray its high dependence on the protection philosophy. Finally, all the ***ECOST*** results indicate (Table 7 and Table 9 text in bold letter), in different ways and from different approaches, that the Case 2 in every considered feeder provides with the lowest outages costs. In conclusion, regardless the ***COC*** models, the decision-making process conduct to the same problem solution.

## ACKNOWLEDGMENTS

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