# Statistical Analysis of Cost of Energy Due to Electricity Outages in Developing Countries

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***Abstract*—This paper describes significant cost saving opportunities for consumers in developing countries by the use of computational intelligence and demand-side-management techniques to mitigate the massive use of diesel back-up during grid outages. We propose novel statistical algorithms to model electricity outages, heavy diesel use and associated customer energy costs in developing countries. Using a blackout simulator and Monte Carlos analysis, we assess the impact of different blackout types such as scheduled, unscheduled and annual forecasted outages on consumer energy costs. Variables for the analysis included time of outage (morning, evening etc.), duration of outage (1-5 hours), Diesel costs (20cents/KW-hr) and type of outage. We found that cost savings opportunities by the use of demand side management to mitigate outages can exceed 30% in many cases.**

***Keywords-computational intelligence; algorithms for energy management; stochastic grid; power outages; energy cost; developing countries***

## I. INTRODUCTION

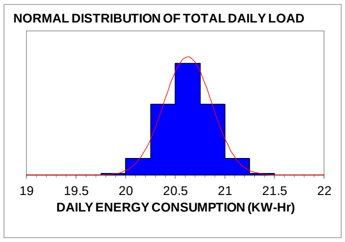
Consumers in developing countries are faced with major challenges with the power grid such as rampant grid outages (Table 1), unreliable power quality with fluctuating voltages and power, uncertain grid restoration schedules, etc. Consumers need to invest heavily in back-up systems (e.g., diesel) and often pay as much as 40-50% of their monthly power bills on back-up diesel costs [1-3]. The customer is often faced with difficult decisions such as whether compromise and curtail his loads or pay high costs of diesel to run his normal loads. There is a lack of computational tools to effectively predict, manage and optimize back-up systems in countries such as India. Also, there is a lack of demand side management approaches to help the consumer to mitigate outages. This study has two goals: one, to statistically model and understand the energy cost behavior caused by a stochastic grid and second, to define the maximum cost-savings potential by the use of demand-side-management techniques.

Risk management for power outages is an enormous challenge for consumers in a developing country. There is the value of lost load, which is essentially the loss that the consumer suffers on account of unsupplied power. The back-up system needs a large capital and recurring operating expenditures. Managing resources such as diesel storage, scheduling factory operations with built-in grid-fail-safe systems, providing adequate and expensive equipment protection including cascading power failures are commonly encountered issues. While diesel generators offer a simple and effective solution, there are many challenges that the emerging market customer needs to address. These mainly include optimal sizing of the diesel systems, minimizing op-ex costs by intelligent forecasting, risk mitigation by proper resource allocation etc. Figure 1 shows a typical model for a grid wherein all the system parameters (power quality, system voltages consumer loads) behave as statistical distributions. Furthermore, one also finds that all dependent parameters such as economic metrics (cost) behave similarly. In this study, we are exploring the use of normal distributions for all system parameters. The paper first proposes a novel approach to model grid outages using different computational techniques, analyzes impact of different outage scenarios on a home consumer and characterize the high energy costs to the consumer by use of diesel. Finally, as a means to cut this high cost, we recommend the use of load optimization or demand-side management and assess the maximum potential savings possible.

TABLE I. RECENT POWER OUTAGES IN INDIA [1]

| Year | Indian City | Power Outage Per Month in Peak Season (Hours) | Type of Power Outage |
|---|---|---|---|
| 2012 | Chennai | 60 | Planned |
| 2012 | Vijayawada | 60 | Planned |
| 2012 | Hyderabad | 90 | Planned |
| 2012 | Haryana State | 150 | Planned |
| 2012 | Jahangirpur | 180 | Planned |
| 2011 | Maharashtra State | 16 | Planned |
| 2011 | Pune | 90 | Unplanned |
| 2011 | Mumbai Suburbs | 7 | Unplanned |
| 2011 | West Bengal Outside Kolk | 150 | Planned |
| 2011 | Gaya | 20 | Unplanned |
| 2011 | Coimbatore | 60 | Planned |
| 2011 | Vijayawada | 60 | Planned |
| 2011 | Madurai | 120 | Planned |
| 2010 | Gulbarga-Bidari | 12 | Unplanned |
| 2010 | Visakhapatnam | 60 | Unplanned |
| 2010 | Chennai | 5 | Unplanned |




**Grid Parameters**
**(Mean μ, Variance $\sigma^2$)**
Grid Availability,
Outages
Power Quality
Consumer Load Profile
& Cost Parameters
Daily Energy

Figure 1. Model for Stochastic Grid Behavior in Developing Countries.

## II. LITERATURE SURVEY

Several studies have focused on the impact of unreliable grids as seen in the following works: An in-depth investigation into the impact of power outages for consumers and businesses in Africa is performed in [4]. This study also assesses the economic consequences of the unreliable grids. A report on real power cost in India [5] reveals that the overall intent of providing cheap and affordable power to the consumers in the country is noble, but if the supplies are inadequate or unreliable, the consumers could actually end up paying a much higher price.

A report from United Nations [6] provides directions to expand access of modern energy services at the household level. An application of combined model of extrapolation and correlation techniques for short term load forecasting of an Indian substation is presented in [7]. Specific opportunities for DSM in the Indian scenario are presented in [8]. Low-cost energy generation using bio-mechanical energy is presented in [9] and this provides technology options for both off-grid users as well as on-grid users who have unreliable power. Specific demand-side-management techniques to mitigate power outages are proposed and assessed in [10]. There is enormous body of literature on the use of demand side management algorithms for power and cost optimization for the end consumer as follows. The use of casual scheduling loads with time-varying prices using stochastic dynamic programming is studied in [11] and its effect on consumer cost are reported. In [13], a power scheduling protocol for demand response in smart grid system is explored which focuses on limiting the allowable power loads. Algorithmic enhancements to a scheduler for residential DSM are presented in [15].

The problem of excessive power outages, its impact to the consumer and mitigation strategies need to be addressed as it is a major painpoint to consumers in developing countries. There are no published algorithmic works that predict the diesel requirements under periodic and rampant outages such as seen in emerging countries. There is also a lack of computation methods in the literature that tackle the problem of load-optimization or demand-response during outage. In this study, we develop computational methods that specifically focus on power outages and quantify their impact using different statistical means. Furthermore, we show the potential savings possible through the use of load optimization.

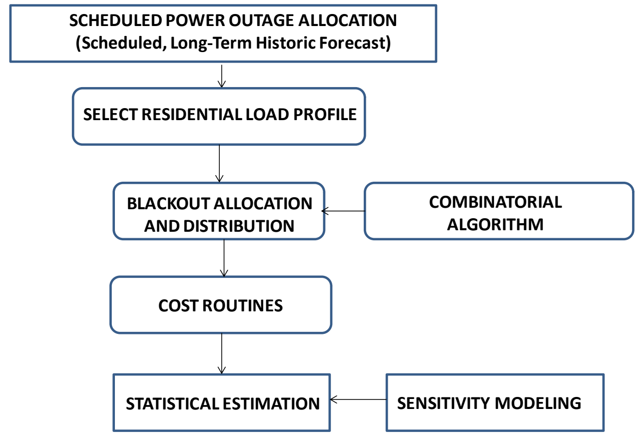



Figure 2(a). Fast Blackout Assessment Tool Architecture.

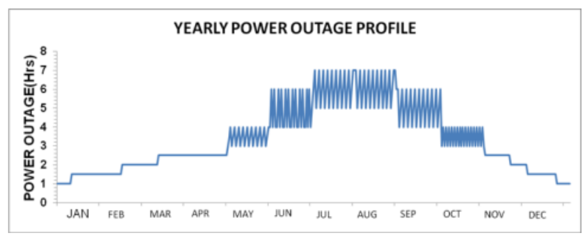



Figure 2(b). Historical Profile of Yearly Outages – Example.

## III. SIMULATION APPROACH

Computational methods used in the present study are described here. To assess different blackout scenarios, a blackout assessment tool is developed (Fig. 2(a)). In this study, we have explored the use of normal distributions to model the different statistical parameters. Based on our data gathered from 20 households in India, normal distribution appears to fit the data well. The types of power outage scenarios modeled we studied include: scheduled, unscheduled and long-term historic forecast. For each case, we study the timing (time of day) and duration of power outage. For long-term forecast analysis, since one does not know that actual distribution of electricity outage, combinatorial algorithms are developed to determine the maximum cost impact. Statistical estimation methods such as Poisson estimation, Monte-Carlo limit analysis are built-in the tool for cost benefit analysis. Output parameters for the tool are statistical distributions for consumer load profile, daily energy consumption, energy costs (e.g. grid cost, diesel cost, daily energy cost), power outages (duration and length), effective cost of power etc.

The key outcomes of the tool are as follows. First, the statistical impact of an unpredictable and uncertain grid combined with usage of diesel back-up is evaluated to determine the actual consumer cost of energy use. Second, maximum cost savings potential that can be achieved by the use of demand-side-management techniques is reported. In the fast analysis tool, the user can select the desired blackout scenario. For example, to perform a scheduled blackout analysis, the user can input a fixed power outage time in a day. The blackout profile is then generated using the user input and the analysis and sensitivity modeling is performed using the cost inputs. An unscheduled power outage can be triggered in a given timeframe or if the user desires, the tool can automatically select create unscheduled outages. Large numbers of profiles (10000) are created for each configuration.

For long-term forecasting, the analysis requires knowledge of historical data. Since most cities in emerging markets do not have organized historical blackout data, a typical power outage profile for a year (Fig. 2(b)) is created for this study. Actual historic data can be input into the tool as required. The Poisson estimator is used to determine the expectation value of blackout duration in a given day. Since the number of ways that this power outage can be distributed in a day is extremely large, the tool uses a combinatorial methodology to allocate the distribution of the blackout. This method is based on the classic balls and bins allocation problem wherein each of the n balls is allocated to a set of m bins in a random, but uniformly distributed, way. The algorithm developed uses an iterative solver combined with a random distributor. The user can generate the specified number of distributions for the required design of experiments. In this study, it was found that 500 iterations are sufficient to provide statistically meaningful data. Nominal costs assumed for the grid is 5c/KWhr and baseline diesel costs assumed in the simulation are 20c/KWhr. The standard deviations assumed are approximately 10%. Sensitivity analysis is performed for diesel cost ratio from 1X to 3X from current diesel costs.

It is useful to calculate an effective cost parameter, $C_{eff}$, which captures the net cost of power to the customer. For a typical supply configuration with the grid and a diesel system, this would provide an average combined cost per unit for the customer. This is valuable to the customer as it provides a way for the customer to quickly estimate his costs, provide insight into quality of the grid by understanding the deviation of cost w.r.t. to the grid ad provide a benchmark and standardized method to compare grid stability and quality across customers and geographical regions. This effective cost parameter can be represented as,

$$C_{EFF} = \text{Daily Cost Per Day/ Energy Consumption}$$
$$= \text{(Grid + Diesel Cost)/Energy Consumption}$$

## IV. RESULTS AND DISCUSSION

The key results of this study are presented in this section. From the consumer viewpoint, several parameters are of interest such as load distribution, distribution of electricity outage duration and timing, daily energy expenditure and increase in energy cost due to diesel usage, fraction of load executed during outage, and finally, the maximum cost savings possible by applying demand-side-management. Baseline cost data for running the loads on grid power are shown in Figure 3 for an Indian home consumer. Sample results from analysis of scheduled power outages are presented in Fig. 4. Herein, we show the results for an outage scenario of 5 hours commencing at 12PM. In all, four different outage start times are simulated and for each, the duration of power outage is varied statistically. The average cost of energy is roughly 2X grid cost (fig. 4(a)) and diesel expenditure (Fig. 4(b)) as a fraction of total energy cost is approximately 66% which is significant. Again, the rise in daily energy cost is a 100% over a grid-only cost.

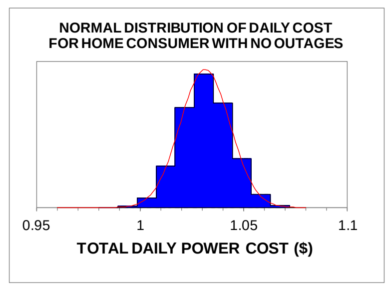
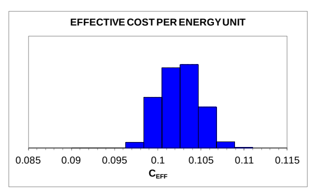
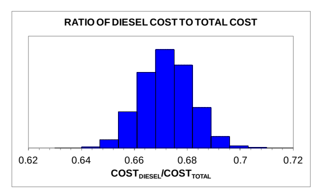
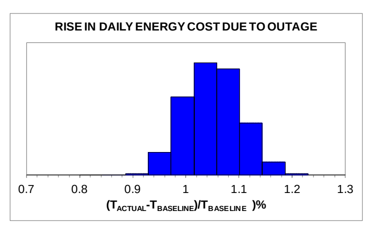



Figure 3. Results of Daily Energy Cost.



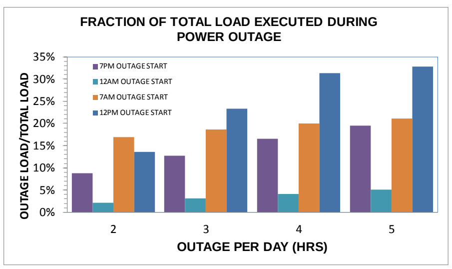




(a) Effective Cost of Energy (b) Ratio Diesel/Total Costs

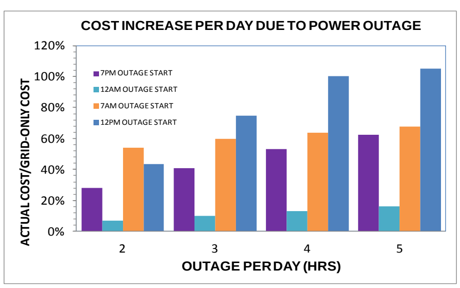



(c) Rise in Daily Energy Cost Due to Outages
Figure 4. Sample Results.

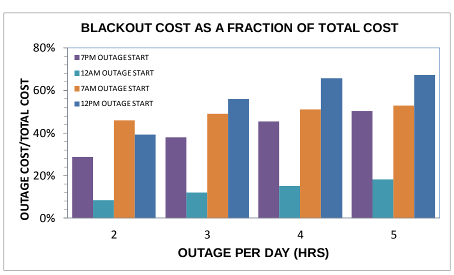
Figure 5 provides further details on the consumer cost and load execution patterns for a residential consumer as a function of the outage time. A power failure during afternoon has the largest impact on consumer costs, followed by morning and evening times. For an outage that is 5 hours long, the maximum load executed is as much as 35% of total daily load and for cases wherein the blackout times are <5 hours, the load fraction can be as high as 25%. An important finding is that in order to execute only 15% of the daily load, the consumer spends as much as 40% of daily total energy cost (Fig. 5(b)). For most power outage scenarios simulated the consumer pays ~40% over the normal grid-only costs for load execution. To execute 30% of the daily load, the consumer cost increases by 2X compared to the baseline case. In other words, a customer in a developing country could spend half of his power expenditure for back-up power during peak seasons when the power outages are incessant. The ratio of diesel costs over the total cost ranges from a typical value of 35% to 65% per day. Maximum diesel usage is either at 7AM or 12PM.




(a) Fraction of Total Load Executed During Outage




(b) Cost Increase Per Day Due to Power Outages




(c) Diesel Usage Cost as Fraction of Total Cost

Figure 5. Key Results of Scheduled Power Outage.

Next, we consider the cases of unscheduled power outages wherein the timing and duration of the outage are random variables (Fig. 6, Table 2). It must be stated that unscheduled power outage generator model needs to be calibrated with local grid conditions and measurements to provide accurate results. In this study, two types of unscheduled power outages are simulated. First, unscheduled power outage distributed through the day as multiple outages and second, the unscheduled random power cuts are limited to a part of the day. Both these scenarios are fairly common in developing countries. As described earlier, a random variable generator is used to simulate the unscheduled power outage scenario. In our model, the average unscheduled power generated is 4.9 hours per day. Unlike scheduled outages, it is difficult to execute power saving approaches such as demand side management during unscheduled blackouts due to its random nature. Stochastic modeling combined with machine learning to refine the predictive models can potentially be used to address the problem of unscheduled power outage management.

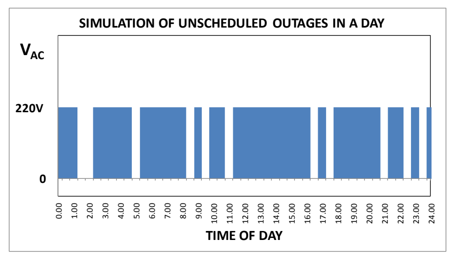



Figure 6. Unscheduled Multiple Power Outages in a Day.

TABLE II. GRID PARAMETERS FOR UNSCHEDULED BLACKOUTS

| UNSCHEDULED POWER OUTAGE TIMING | FRACTION OF LOAD EXECUTED DURING OUTAGE | COST INCREASE/ DAY | DIESEL COST/TOTAL COST |
|---|---|---|---|
| ENTIRE DAY | 20% | 64% | 49% |
| 7PM - 10PM | 2% | 8% | 9% |
| 12AM-3AM | 1% | 2% | 2% |
| 7AM-10AM | 4% | 12% | 12% |
| 12PM-3PM | 4% | 47% | 28% |

TABLE III. MAXIMUM COST SAVINGS POTENTIAL BYUSING DEMAND-SIDE TECHNIGIES

| | MAXIMUM POSSIBLE COST SAVINGS BY LOAD-SHIFTING | | | |
|---|---|---|---|---|
| | POWER OUTAGE START TIME | | | |
| OUTAGE (HRS) | 7PM | 12AM | 7AM | 12PM |
| 2 | 22% | 6% | 35% | 40% |
| 3 | 28% | 9% | 37% | 42% |
| 4 | 34% | 11% | 38% | 49% |
| 5 | 38% | 14% | 40% | 50% |

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TABLE IV. EFFECTIVE COST PARAMETER PER UNIT OF ENERGY DUE TO OUTAGE

| | EFFECTIVE COST PARAMETER $C_{EFF}$ | | | |
|---|---|---|---|---|
| | POWER OUTAGE START TIME | | | |
| OUTAGE (HRS) | 7PM | 12AM | 7AM | 12PM |
| 2 | 0.06 | 0.05 | 0.08 | 0.07 |
| 3 | 0.07 | 0.05 | 0.08 | 0.09 |
| 4 | 0.08 | 0.06 | 0.08 | 0.10 |
| 5 | 0.08 | 0.06 | 0.08 | 0.10 |

TABLE V. SENSITIVITY ANAYSIS OF COST PARAMETERS DUE TO OUTAGES

| | COST INCREASE | | BLACKOUT COST/TOTAL COS | | MAX. SAVINGS BY DSM | |
|---|---|---|---|---|---|---|
| DIESEL PRICE | 2 HRS | 5 HRS | 2 HRS | 5 HRS | 2 HRS | 5 HRS |
| Current | 43% | 105% | 39% | 67% | 40% | 50% |
| 1.25X | 54% | 130% | 43% | 71% | 35% | 57% |
| 1.5X | 68% | 164% | 48% | 75% | 40% | 62% |
| 2X | 95% | 230% | 55% | 80% | 49% | 70% |
| 3X | 150% | 361% | 65% | 85% | 60% | 78% |

Finally, we show that the high power back-up costs due to use of diesel during electricity outages can be significantly mitigated through the use of intelligent scheduling or demand-side-management (DSM) techniques such as load shifting, peak-shaving and valley-filling. These techniques enable the user to execute the full load requirement with simultaneous cost savings. Since grid power is typically inexpensive, the purpose of the demand-side-management method is to shift the loads to the grid when it is available. As a result, the maximum cost savings potential is calculated when the entire load is shifted outside the power outage region and executed on grid power. However, in reality, the actual savings will be dictated by the specific distribution of schedulable and interruptible loads. The present data provides an upper limit achievable for the demand response schemes and the actual implementation of the DSM during power outages is presented in [10]. The maximum potential savings possible is generally upwards of 30% for most cases modeled (Table 3) and maximum DSM gains are possible when the power outage occurs during the afternoon. Measure of the grid cost disparity is given in Table 4 through the effective cost parameter. The efficiency of a demand-side management scheme is measured by how close the effective parameter is to the grid cost. For most cases in the present study, the grid disparity ranges from 1.5X to 2X the cost of per unit of grid power. Table 5 shows the sensitivity analysis using an increasing cost of diesel (varied from 1X to 3X to the current cost of diesel). The energy costs, based on this sensitivity analysis, show that, the effective cost of power can be upwards of four times the cost of a grid supported load. Such high costs can currently be seen in remote locations wherein availability and accessibility to diesel fuel is a challenge. As expected, the corresponding potential for load optimization is also high.

Long-term forecasting using historical data enables system planners to mitigate business risks due to grid uncertainty. Unfortunately, such historical data is largely not available except for a few areas. It is anticipated that upon the advent of the smart grid, highly localized behavior models of the grid will be available for the customer. In this study, we show a methodology to analyze historical data to predict annual diesel estimates for the consumer. Using combinatorial algorithms, one can generate different blackout scenarios. The costs are calculated for each individual case and statistical analysis is performed on the entire set of data. This is used to forecast diesel projections for an entire year as represented in Fig. 7. Overall, in summer months of May till November, users incur heavy cost due to power outages.

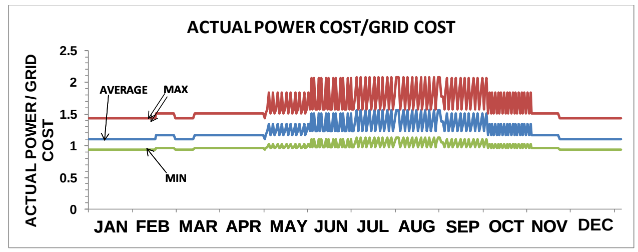


Figure 7. Forecasting of Yearly Cost for Home Consumer.

## V. CONCLUSIONS

Computational intelligence methods are used to explore the problem of rampant power outages and associated high diesel back-up costs in developing countries. Using consumer load profiles, outage information and energy cost information, we show that in order to execute only 15% of the daily load, the consumer spends as much as 40% of the daily total energy cost. Further, to execute 30% of the daily load, the consumer cost roughly doubles. That is, a customer in a developing country could spend half of his power expenditure for back-up power during peak seasons when the power outages are incessant. In the case of unscheduled outages caused by random system failures, Monte Carlo analysis shows that the cost impact to the customer can be anywhere as much as 60% more than normal operation. Similar behavior is also seen for annual forecasting of power outages and consumer costs. Assessment of the maximum cost-savings potential using demand-side-management methods is seen to be huge and upwards of 30%.

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