MINIMIZATION OF COSTS ASSOCIATED WITH POWER SUPPLY DISRUPTIONS BY BUILDING RESILIENCE IN ELECTRIC POWER DISTRIBUTION SYSTEMS

Beatriz Sales da Cunha
biasales.c@gmail.com
Helder Henrique Lima Diniz
helderhld@gmail.com
Márcio das Chagas Moura
marcio@ceerma.org
Isis Didier Lins
isis.lins@ceerma.org
Vicente Ribeiro Simoni
vicente.simoni@gmail.com

Electric Power Distribution systems (EPDS) are defined as Critical Infrastructure (CI) systems as they provide services fundamental to the economy and routine of society, supporting the operation of other systems. Given EPDSs complex infrastructure and increasing exposure to natural hazards, such as extreme weather events, earthquakes, floods and wildfires, there is a growing interest on the evaluation of power grid resilience enhancement. In this context, this paper proposes a Mixed-Integer Linear Programming (MILP), with the aim to determine which EPDSs’ resilience enhancement strategies should be adopted in order to minimize cost, considering a potentially extreme set of disturbances. An application example was conducted, considering an EPDS for industrial clients. Results point towards resilience potential to minimize power interruptions and reduce total expected additional costs, although proving that it is economically unfeasible to ensure total demand supply given the occurrence of disruptions in normal operation. Therefore, an analysis of different service level goals was conducted in order to compare the advised strategies for each case.

Palavras-chave: Resilience, Electric Power Distribution Systems (EPDS), Power interruption, Service level
1. Introduction
Critical Infrastructure (CI) systems are characterized by providing services fundamental to the economy and routine of society, such as distribution of power, water, oil and material supplies (MOURA et al., 2017). Electric Power Distribution Systems (EPDSs) are especially critical since they support the operation of other systems. According to Liévanos and Horne (2017), the U.S. EPDS serves more than 100 million customers and 283 million people, with more than 1 trillion dollars in asset value.

Between 2003 and 2012, 58% of power outages in the U.S. were caused by extreme weather events, such as Hurricane Katrina, and super-storm Sandy. For the manufacturing industry sector, for example, power outages may affect productions’ volume, quality, lead time and stock (U.S. DEPARTMENT OF ENERGY, 2013). Thereby, a vulnerability analysis needs to take into account EPDSs’ design and operation in order to cope with low probability/high-impact disturbances (ROEGE et al., 2014).

Given EPDSs complex infrastructure and increasing exposure to natural hazards, such as extreme weather events, earthquakes, floods and wildfires, there is a growing interest on the evaluation of power grid resilience enhancement through hardening and operational measures (TRAKAS; HATZIARGYRIOU, 2018). This paper adopts the concept of system’s resilience as the ability to withstand, adapt and rapidly recover from disturbances on system performance, as to reduce both magnitude and duration of the impact (TURNQUIST; VUGRIN, 2013; LIÉVANOS; HORNE, 2017).

Resilient EPDSs should be built with “fault-tolerance, fast response, recovery and reliability” (TRAKAS; HATZIARGYRIOU, 2018, p. 2261), calling attention to the definition of pre-event strategies that enables improvements in network performance, which can be measured by the service level, the regularity and the quality of power supply (MOURA et al., 2017). Considering EPDSs for industrial clients, this paper aims at determining possible EPDSs’ resilience enhancement strategies and applying a quantitative model that determines which strategies should be adopted in order to minimize cost, considering a potentially extreme set of disturbances. In this case, cost is composed by:

- Investments in resilience strategies;
- Additional costs due to disturbances;
- Recovery costs.
An application example is shown in Section 4 to illustrate the applicability of the proposed model and to evaluate resilience investments to minimize power interruptions and reduce costs.

The rest of this paper is organized as follows: Section 2 provides the theoretical background of resilience and its application on EPDSs. Section 3 presents the EPDS configuration characteristics and the formulation of the proposed model. Section 4 discusses the application example results. Finally, Section 5 summarizes and concludes this paper with remarks.

2. Theoretical background
In the field of Risk Management, while the preventive attitude aims at eliminating or reducing the probability of risk occurrence, the reactive attitude is effect-oriented and, thus, strives for mitigating the negative impact of disruptive events (THUN; HOENIG, 2011). The latter does no act on the risk itself, but on building system’s capacity to absorb disturbances. In this context, resilience assessment emphasizes an evaluation of systems’ ability to anticipate and absorb potential disturbances, accommodate internal or external changes to normal operation, and establish response behaviors towards building the capacity to withstand disturbances or to rapidly recover the system (FRANCIS; BEKERA, 2014).

Therefore, the incorporation of resilience to a system can be accomplished through pre-event investments, which correspond to the inclusion of three different capacities: absorptive (anticipate and absorb disturbances to withstand and minimize its consequences), adaptive (rearrange network structure) and restorative (speed and ease by which the system returns to normal operation) (TURNQUIST; VUGRIN, 2013; LABAKA; HERNANTES; SARRIEGI, 2015; FRANCIS; BEKERA, 2014).

When determining pre-event strategies that enables resilience enhancement, and hence mitigation of disruptions’ impact, it is important to evaluate the potentially extreme set of events the system might be exposed to (SHAO et al., 2017). In fact, the impact of disruptions on systems’ performance depends on the characteristics of both the incident and the system configuration (THUN; HOENIG, 2011).

Applications of resilience assessment can be observed in infrastructure systems (FILIPPINI; SILVA, 2014), safety management systems (DINH et al., 2012), socio-ecological systems (CHOPRA; KHANNA, 2014), and economic systems (VUGRIN et al., 2010). Specifically, applications of resilience on EPDS are described below.

Liévanos and Horne (2017) focus on who is affected by failures in electric grid resilience, suggesting the existence of “unequal resilience” by showing that socially disadvantaged
neighborhoods tend to experience greater power outages than advantaged neighborhoods. Roege et al. (2014), on the other hand, advocate that energy supply resilience planning needs to consider the distinction of clients’ responsibilities, such as hospital and military installation for example, as well as system dynamics.

Trakas and Hatzigioryiou (2018) proposed a model to optimize power supply and minimize generation cost, considering the damage caused by wildfires and resilience enhancement actions. Shao et al. (2017) proposes a mathematical model to minimize the investment and the operation costs of an EPDS, considering its exposure to extreme events and the possibility of hardening the system by replacing overhead power grid by underground ones.

In light of these applications, this paper aims to evaluate the performance and response of an EPDS to industrial clients, under the consideration of a set of possible disturbances and of a set of resilience enhancement actions, and minimize cost associated with:

- Investments in resilience strategies;
- Additional costs due to disturbances;
- Recovery costs.

3. Model description
This paper applies a Mixed-Integer Linear Programming (MILP), based on the model developed by (MOURA et al., 2017) to EPDSs for industrial clients, that aims to minimize total expected additional cost, given a set of possible disturbances and a set of resilience enhancement actions, which are described below. The scope of the analysis is shown in Figure 1, corresponding to a generic EPDS in which, under normal conditions, each industrial client ($C_i$) has a demand $Q_i$ supplied by a specific SS$_j$ (primary assignment) with capacity $K_j$.

In fact, power delivery in this case works as a system in series, composed by transmission lines and step-down substations (SSs) where both are considered to be vulnerable to disturbances and thus can be fully or partially operational.

Figure 1- Generic EPDS configuration

Source: Moura et al. (2017)
The sum of the costs associated with investments to promote system’s resilience is called Investments in Design for Resilience (IDR) and is calculated in Equation 1. The first term indicates the investment in absorption, represented by the cost of adding capacity to each substation. The next three terms indicate the investments in adaptive capacity, represented by the costs of installing diesel generators for clients, establishing backup connections between clients and substations that are not primary connected and switching from overhead to underground lines, respectively. The remaining terms are related to investments in recovery capacity, comprising the costs of increasing the recovery rate for both substations and lines. All variables and parameters are described at the Appendix in Table 1 and Table 2, respectively.

\[
IDR = \alpha \sum_{j} A_j + \gamma \sum_{i} n_i + \lambda \sum_{i,j} B_{ij} + \phi \sum_{i,j} H_{ij} + \mu \omega + \eta \delta
\]  
(1)

\[
IS = \sum_{c} p_c \left[ \delta \sum_{i,j} Q_{ij} + \sum_{i} \phi_1 Q_i + \sum_{i} \phi_2 Q_i + \sum_{i} \phi_3 Q_i + \rho \sum_{i} Q_i \sum_{j} (1 - \lambda_{ij}) \sum_{c} x_{ijtc} \right]
\]  
(2)

\[
PCR = \sum_{c} p_c \left[ \pi \sum_{i,j} R_{ijtc} + \sigma \sum_{i} \sum_{j} \sum_{c} \alpha_{ijtc} \right]
\]  
(3)

Given a set of possible disturbances in the energy supply system, each with probability \( p_c \), Equation 2 specifies the expected additional costs to normal operation, called Impact on the System (IS), comprising the costs of: energy supply via diesel generators, demand supply below contracted service level, not reestablishing normal supply before the deadline \( d \), and energy supply via backup connections, respectively. Finally, Equation 3 represents the expected cost of restoring system’s performance after an interruption, called Post-interruption Recovery Cost (PCR), considering recovery actions displayed for substations and lines. Equation 4 specifies the objective function of minimizing the Total Expected Additional Cost (TEAC) associated with system’s resilience to disturbances, and Equations 5 to 28 represent model’s constraints.

\[
\text{Minimize } TEAC = IDR + IS + PCR
\]  
(4)

Subject to:

\[
\sum_{j} B_{ij} \leq 1 \quad \forall i
\]  
(5)
\[ L_{ij} + B_{ij} \leq 1 \quad (6) \]
\[ L_{ij} - H_{ij} \geq 0 \quad (7) \]
\[ \sum_{j} x_{ijtc} + z_{tec} + y_{tec} = 1 \quad \forall i, t, c \quad (8) \]
\[ z_{tec} Q_{t} \leq u_{t} G \quad \forall i, t, c \quad (9) \]
\[ x_{ijtc} \leq O_{ijtc} + B_{ij} \quad \forall i, j, t, c \quad (10) \]
\[ \sum_{i} x_{ijtc} Q_{t} \leq U_{jtc} \quad \forall j, t, c \quad (11) \]
\[ o_{ijtc} \leq (1 - F_{ij}) L_{ij} + \sum_{i=1}^{t-1} a_{ijtc} + H_{ij} \quad \forall i, j, t, c \quad (12) \]
\[ o_{ijtc} \leq L_{ij} \quad \forall i, j, t, c \quad (13) \]
\[ o_{ijtc} = L_{ij} \quad \forall i, j, c \quad (14) \]
\[ U_{jtc} = (1 - V_{j}) (K_{j} + K_{j} A_{j}) + \sum_{t=1}^{i-1} R_{jtc} \quad \forall j, t, c \quad (15) \]
\[ U_{jtc} \leq K_{j} + K_{j} A_{j} \quad \forall j, t, c \quad (16) \]
\[ U_{jtc} = K_{j} + K_{j} A_{j} \quad \forall j, t, c \quad (17) \]
\[ \sum_{j} R_{jtc} \leq r + w \quad \forall t, c \quad (18) \]
\[ \sum_{i} \sum_{j} a_{ijtc} \leq l + d \quad \forall t, c \quad (19) \]
\[ y_{tec} = b_{tec} (1 - TL) + b_{tec} \quad \forall i, t, c \quad (20) \]
\[ b_{tec} \leq e_{tec} \quad \forall i, t, c \quad (21) \]
\[ b_{tec} \leq e_{tec} \quad \forall i, t, c \quad (22) \]
\[ b_{tec} \leq e_{tec} \quad \forall i, t, c \quad (23) \]
Connections between clients and substations take the form of transmission lines that can be either given by the original network design (primary connections) or defined by the model as a backup connection to incorporate flexibility to disturbances on the original network design (Constraint 6). However, the former is limited to one per client (Constraint 5). Moreover, transmission lines can be set over-head or underground (Constraint 7) as a measure to reduce the network vulnerability to extreme conditions and natural disasters (SHAO et al., 2017).

Constraint 8 specifies that clients’ demands can be met by the substations they are connected to ($x_{ijtc}$) or by diesel generators ($z_{itc}$). Whilst former relies on the addition of diesel generators (Constraint 9), the prior considers whether the connection is operational and the substation capacity is available (Constraints 10-11). Given a disruptive event and considering that the connection exists ($L_{ij}$), an over-head primary connection is recovered at the rate represented by $a_{ijtc}$ (Constraint 12-14). Underground transmission lines, on the other hand, do not suffer from these disturbances.

The available capacity of each substation follows the same reasoning (Constraints 15-17). Therefore, given $K_j + K_i A_j$, substations’ capacities can be affected by disturbances and, hence, should be fully recovered over time, increasing the capacity by the rate of $R_{itc}$. The network recovery performance depends on the available resources for this activity, that are shared among all substations and lines (Constraints 18-19). Note that the capacity recovered in time $t$ is only available in time $t+1$.

Constraints 20-25 indicates the incorporation of the artifice called “Special Ordered Sets-Type 2”, used to represent the function illustrated in Figure 2 in a linear format. Note that SL is a metric applied to the demand supply of each client in each period, not for the sum of all demands. Finally, constraints 26-28 specifies the variables boundaries.
The main contributions of this paper in comparison to the model proposed by (MOURA et al., 2017) are:

- A modified Impact on the System (IS) metric, that only considers the additional costs, caused by disturbances, to normal operational costs. As resilience is associated with the capacity of reducing disturbances’ consequences (TURNQUIST; VUGRIN, 2013; LIÉVANOS; HORNE, 2017), improving resilience can be achieved by reducing the gap between normal operation and operation under disturbances, and hence, minimizing IS.

- The evaluation of the trend between over-head and underground lines, conversely to the possibility of adding redundant transmission lines (stand-bys), due to its potential to reduce power grid vulnerability to extreme conditions and natural disasters (SHAO et al., 2017);

- The incorporation of the concept of service level to the model, as one of the future research gaps proposed by (MOURA et al., 2017);

- The possibility of increasing recovery capacity for lines failures, following the same reasoning of SS recovery capacity and in accordance with D’Lima and Medda (2015) definition of resilience as “the speed at which a system returns to equilibrium after a disturbance away from equilibrium”.

4. Application example
Figure 3 represents the power supply network considered for the application of the proposed model, composed by substations and industrial clients, in which supply equals demand. In this case, we considered that clients can be on the chemical/petrochemical (P), manufacturing (M) or food (F) segment, with demand of 15 MVA/period, 10 MVA/period and 5 MVA/period, respectively. The industry sector determines clients’ importance and this information is
incorporated to the model through different penalizations for failure in demand supply, as shown at the Appendix in Table 2. Due to network exposure to disruptive events, we aim at improving network resilience, showing its potential to minimize power interruptions and reduce total expected additional costs.

Figure 3 – Illustration of the application example

In addition to data extracted from (MOURA et al., 2017), including parameters values and network configuration, the parameters shown at the Appendix in Table 2 were used to conduct a numerical example. This paper is not concerned about characterizing the specific disturbing events the network might be exposed to, on the contrary, we aim at evaluating and minimizing the consequences of how the network may become unavailable. For this purpose, the approach proposed by (MOURA et al., 2017) considers a set of scenarios involving the combination of the following situations for substations and lines status: no failure; a single failure; or combination of two failures. According to this approach, 192 scenarios were defined for this example, including the scenario in which none component is affected by disturbances (“no failure” scenario), and probabilities were defined considering that some scenarios are more likely than others and that the probability sum for all 192 scenarios equals 1.

4.1 Probability analysis
Considering the parameters data at the Appendix in Table 2, we analyzed three different cases by varying the probability of the “no failure” scenario and splitting the complimentary
probability for the remaining 191 scenarios. For cases 1, 2 and 3 we considered 0.9, 0.5 and 0.0, respectively, as the probability for the “no failure” scenario. For each case, the total expected cost is presented in Figure 4, comparing the situations with the possibility of investing in the resilience actions proposed by this paper (“With IDR”) against without the consideration of resilience investment options (“Without IDR”). As expected, no investments in resilience are advised for case 1 since the probability of any failure occurrence is very low. Total expected cost and IDR are more than two times greater from case 2 to case 3, considering “With IDR”. For case 2, IDR includes the addition of line recovery capacity, allowing 1 line to be recovered per period. For case 3, in addition to that, an underground transmission line between SS$_2$ and P$_3$ is established, which is reasonable given this client importance.

Figure 4 – Total cost for cases 1, 2 and 3

Even though total cost is increasing, IS participation percentage on total cost decreases from 97% in case 1 to 81% in case 3, while PCR percentage keeps steady. In addition, from “With IDR” to “Without IDR”, total expected cost is 165% greater for case 2 and 184% greater for case 3. These facts highlight IDR potential to reduce total expected additional costs.

4.2 Service level analysis
To further the analyses of this model, the scenario consisting of the combined SS$_1$ and SS$_2$ failures was chosen to assess the influence of specifying a goal for clients’ service level on IDR and, hence, on total expected additional cost. For this analysis, we considered the occurrence of this specific scenario, whose results are presented in Figure 5. As highlighted before, IDR has the potential to reduce total expected additional costs, as it reduces the gap
between SL and the actual demand supplied. Therefore, as expected, Figure 5 shows that higher SLs justify higher IDR.

It is important to note that the average IDR participation on total expected cost is 70% (standard deviation of 2.4%) while IS decreases 50% from SL = 1 to SL = 0.5. This fact indicates that the reduction on penalization, due to SL decrease to 0.5, does not affect the financial resources spent on IDR. However, it affects the allocation of these resources, as shown in Table 2.

![Figure 5 – Total cost for different SL goals](source: Authors)

For greater service levels, resilience investments are focused on building absorptive and adaptive capacity. As service levels decrease, investments shift to adaptive and restorative capacities. The reasoning behind this attitude proves that absorptive and adaptive capacity enable more effective response. For example, for chemical/petrochemical clients, power interruptions usually cause work-in-progress to lose specification. In this case, generators can manage work-in-process, allowing the system to restart without any further delays when normal power supply returns. However, as shown in Table 2, it is economically unfeasible to ensure total demand supply given the occurrence of disruptions in normal operation (MOURA et al., 2017).

It is worth noting that although for an SL of 0.6 and 0.5 no capacity is added for SS3, it still serves as backup for some chemical/petrochemical clients at the expense of its own clients. This action intends to reduce IS given the importance of these clients and clearly supports the existence of “unequal resilience”, where “the return to system equilibrium is unevenly experienced” throughout clients (LIÉVANOSA; HORNE, 2018, p. 202).
Table 2 – Service analysis main results

<table>
<thead>
<tr>
<th>Decision metrics</th>
<th>1</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recovery rate</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>11</td>
</tr>
<tr>
<td>Generators</td>
<td>22</td>
<td>17</td>
<td>10</td>
<td>4</td>
<td>25</td>
<td>19</td>
</tr>
<tr>
<td>Additional capacity</td>
<td>SS₃</td>
<td>SS₃</td>
<td>SS₃</td>
<td>SS₃</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Backup connections</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td>9</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Total supply</td>
<td>99%</td>
<td>97%</td>
<td>95%</td>
<td>92%</td>
<td>90%</td>
<td>88%</td>
</tr>
</tbody>
</table>

Source: Authors

Although the greater investment on increasing substations recovery capacity was defined for SL = 0.5, Figure 6 shows that SS₁ and SS₂ capacities where fully reestablished between the 4th and 5th period for all SL goals considered. However, as shown in Figure 6(f), recovery resources are evenly shared between the two substations for SL = 0.5.

Figure 6 – SS₁ and SS₂ recovery dynamics across different SL goals

Source: Authors
5. Conclusion
This paper proposed a Mixed-Integer Linear Programming (MILP), based on the model developed by (MOURA et al., 2017) to EPDSs for industrial clients, that aims to minimize total expected additional cost, given a set of possible disturbances and a set of resilience enhancement actions, which are described in Section 3.

The contributions of this paper to the model proposed by (MOURA et al., 2017) include: the consideration of only additional costs, the possibility of shifting from over-head to underground transmission lines, the specification of service level goal, and the possibility of investing in recovery capacity of transmission lines.

The results presented suggest that resilience has the potential to minimize power interruptions and reduce total expected additional costs. On the other hand, they also indicate that it is economically unfeasible to ensure total demand supply given the occurrence of disruptions in normal operation. In this context, the concept of “unequal resilience” rises, as resources need to be allocated according to clients’ importance, as a way to minimize economic impact and promote network overall resilience. The analysis of different service level goals highlights that investments in absorptive and adaptive capacities enable more effective response than investments on recovery.

Nevertheless, a paper limitation relies on the consideration of the objective function as a weighted average of costs, given the probability of each scenario. As a matter of fact, low-probability/high-consequences as opposed to high-probability/low-consequences would have the same weight for the objective function. Hence, future research aims at developing a multi-objective optimization model considering resilience and other trends for CIs.

6. Acknowledgements
Authors would like to thank the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPQ).

REFERENCES


**APPENDIX**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Range of unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_j$</td>
<td>Addition of $K_j$ units to the capacity of SS$_j$</td>
<td>MVA</td>
</tr>
<tr>
<td>$n_i$</td>
<td>Quantity of generators added to C$_i$</td>
<td>units</td>
</tr>
<tr>
<td>$B_{ij}$</td>
<td>Backup connection between C$_i$ and SS$_j$</td>
<td>0 or 1</td>
</tr>
<tr>
<td>$H_{ij}$</td>
<td>Establishment of an underground line between C$_i$ and SS$_j$</td>
<td>0 or 1</td>
</tr>
<tr>
<td>$w$</td>
<td>Additional resources for SS recovery</td>
<td>MVA/period</td>
</tr>
<tr>
<td>$d$</td>
<td>Additional resources for line recovery</td>
<td>Line/period</td>
</tr>
<tr>
<td>$x_{itc}$</td>
<td>Portion of C$_i$ demand supplied by generators in period $t$ of scenario $c$</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$x_{itc}$</td>
<td>Portion of C$_i$ demand supplied by SS$_j$ in period $t$ of scenario $c$</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$y_{itc}$</td>
<td>Portion of C$_i$ demand that is not supplied in period $t$ of scenario $c$</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$U_{itc}$</td>
<td>Capacity of SS$_j$ available in period $t$ of scenario $c$</td>
<td>MVA</td>
</tr>
<tr>
<td>$R_{itc}$</td>
<td>Capacity of SS$_j$ recovered in period $t$ of scenario $c$</td>
<td>MVA</td>
</tr>
<tr>
<td>$a_{itc}$</td>
<td>Portion of the line between C$_i$ and SS$_j$ recovered at time $t$ of scenario $c$</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$Q_{itc}$</td>
<td>Operation status of the line between C$_i$ and SS$_j$</td>
<td>0 or 1</td>
</tr>
<tr>
<td>$b_{ntc}$</td>
<td>Auxiliary variable for the “Special Ordered Sets-Type 2” artifice</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$e_{ntc}$</td>
<td>Auxiliary variable for the “Special Ordered Sets-Type 2” artifice</td>
<td>0 or 1</td>
</tr>
</tbody>
</table>

Source: Adapted from Moura et al. (2017)
### Table 2 – Parameters description and value

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>Cost for adding 50 MVA of capacity to SSs</td>
<td>$ 3 million</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Cost of installing a diesel generator</td>
<td>k$ 260</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Cost of backup establishment</td>
<td>k$ 480</td>
</tr>
<tr>
<td>( \varphi )</td>
<td>Cost of building an underground line</td>
<td>k$ 400</td>
</tr>
<tr>
<td>( \mu )</td>
<td>Cost of adding resources to accelerate SSs’ recovery</td>
<td>k$ 100 / MVA</td>
</tr>
<tr>
<td>( \eta )</td>
<td>Cost of adding resources to accelerate lines’ recovery rate</td>
<td>k$ 600 / line</td>
</tr>
<tr>
<td>( \theta )</td>
<td>Cost of demand supply from diesel generators</td>
<td>k$ 12 / MVA</td>
</tr>
<tr>
<td>( \phi_i )</td>
<td>Penalty for demand supply of C, below SL</td>
<td>k$ 300 / MVA (P),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>k$ 270 / MVA (M),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>k$ 240 / MVA (F)</td>
</tr>
<tr>
<td>( \delta_i )</td>
<td>Penalty for unmet demand of C, after a certain deadline ( d )</td>
<td>k$ 200 / MVA (P),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>k$ 180 / MVA (M),</td>
</tr>
<tr>
<td></td>
<td></td>
<td>k$ 160 / MVA (F)</td>
</tr>
<tr>
<td>( \rho )</td>
<td>Cost of demand supply from backup connection</td>
<td>k$ 10 / MVA</td>
</tr>
<tr>
<td>( \pi )</td>
<td>Cost of SSs’ recovery</td>
<td>k$ 15 / MVA</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>Cost of subtransmission lines recovery</td>
<td>k$ 100 / line</td>
</tr>
<tr>
<td>( T )</td>
<td>Time horizon</td>
<td>8 hours</td>
</tr>
<tr>
<td>( d )</td>
<td>Deadline for return to normal supply</td>
<td>3 hours</td>
</tr>
<tr>
<td>( r )</td>
<td>Recovery rate for SSs’ capacities</td>
<td>20 MVA/hour</td>
</tr>
<tr>
<td>( l )</td>
<td>Recovery rate for subtransmission lines</td>
<td>0.5 line/hour</td>
</tr>
<tr>
<td>( G )</td>
<td>Diesel generator capacity</td>
<td>2 MVA</td>
</tr>
<tr>
<td>( SL )</td>
<td>Service level goal</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Adapted from Moura et al. (2017)