# Smart Grid Reconfiguration based on Prediction Model for Technical Teams Intervention Integration and Recovery Enhancement

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Abstract:     To overcome the problem of critical failures recovery and improve reliability, quality of service and recovery performance, it is essential to provide and apply a new oriented solution for smart grid reconfiguration. This solution allows for resolving the problem of the late intervention of technical teams and the insufficiency of energy for recovery, by implementing a prediction model that assists the integration of a number of technical teams. In addition, it estimates the newly added number of emergency lines coming from new integrated renewable sources. This heuristic is programmed based on the linear programming and the simplex algorithm. This approach is implemented in python as a tool called SGREP, then tested and validated at run-time on four real different smart grids. Thereby, the proposed solution improves the guaranteed gains in terms of power availability, waiting time and financial cost.

## 1 INTRODUCTION

The smart grid is defined as a real meshed power network of electrical components and lines, specifically it includes three voltage levels: high, medium and low. In the context of failures detection and restoration, a study in (Iqbal and Kütt, 2018) has investigated the power demands of clients by establishing a new model that estimates power quality characteristics in residential buildings. They have measured the consumer energy demand using the web of things for personalized loads forecasting in (Ding et al., 2014).

Authors in (Ben Meskina et al., 2016) have supervised and controlled smart grids through a multi-agent system with variant smart devices and sensors and integrates new emergency lines coming from a central power plant. In (James et al., 2017), a proposed scheme is provided for determining the fault type, phase, and location for the protection of micro-grid and the recovery of failures. In (Ben Meskina et al., 2018), a reconfiguration solution is proposed to identify consumers that may play the role of feeders by adding new emergency lines between consumers.

However, researchers in (Bhalshankar and Thorat, 2016) have addressed the effective role of the integration of renewable sources to improve the growth of

power demand. Researchers in (Abidi et al., 2017) have created a mathematical model that works for energy balancing between the production and the consumption of loads in micro-grids. In (Worighi et al., 2019), authors have briefly proposed a virtual system for the integration of solar power generation units and battery storage systems with the proposed architecture along with control strategies.

Authors in (Nefedov et al., 2018) have developed an electric vehicle that uses renewable energy sources to support great prosumer buildings in case of interruptions and outages. In (Ziouche et al., 2019a), workers have provided a linear regression prediction model that defines the accurate number of new integrated renewable sources to a studied smart grid according to a given budget by the electricity market. In (Ziouche et al., 2019b), researchers have implemented a new cloud-based architecture for smart grid rebuilding where we have worked on scheduling technical teams interventions and estimation of available renewable energy in sources for failures recovery.

In (Vaidya and Kasturiwale, 2016), researchers have dealt with giving the solution of solving two-phase problems with the simplex methods that work for the resolution of linear programming problems.

Nowadays, smart power systems aim to enhance

security, reliability, recovery performance and quality of service. Critical clients such as hospitals, commercial buildings and research laboratories suffer from a miss of electricity in case of blackouts and outages, which causes a set of problems such that:

- The insufficient number and late intervention of technical teams because they are not specialized or busy in repairing other urgent failures.

- The slow intervention of technical teams that causes the growth of total waiting time.

- The self-insufficiency of available energy for recovery of critical failures in repairing.

In order to resolve the above problems, we propose a global reconfiguration that is applied in two steps:

- The first step is to integrate and predict the accurate number of expert and technician teams needed to fix all the failures in the smart grid, then apply run-time scheduling.

- The second step is to provide a new number of emergency lines to reduce clients waiting time without electricity.

Based on this contribution, we propose in this paper a new approach that permits (i) to cover multiple uncovered failures, (ii) to bring a defined number of technical teams: « expert teams that works for hard failures maintenance and technician teams that repair easy failures », and (iii) to integrate new emergency lines at real-time from renewable sources. We implement a tool called SGREP for smart grid reconfiguration and to demonstrate the effectiveness and robustness of this strategy in order to guarantee best recovery in terms of power availability and waiting time.

The remainder of this paper is organized as follows: Section 2 surveys the formalized requirements of the problematic. Section 3 discusses the contribution of reconfiguring strategy. Section 4 considers a case study and shows the obtained gains in terms of power availability and total waiting time. Section 5 concludes the paper and provides a brief suggestions for the future work.

## 2 SMART GRID MODEL

In this section, we formalize the smart grid structure and parameters.

### 2.1 Smart Grid Formalization

A smart grid $SG$ is considered as a graph of electrical components and electrical lines, i.e.,

$$SG = G(C, L) \qquad (1)$$

where $C$ is the set of electrical components that includes a set of power generators $PG$, a set of transformers $TRANS$ and a set of consumers $CONS$, i.e.,

$$\begin{cases} C = PG \cup TRANS \cup CONS \\ PG = PS \cup RS \\ TRANS = MVT \cup LVT \\ CONS = MC \cup LC \end{cases} \qquad (2)$$

where $PS$ is the central power plant and $RS$ is the set of existing renewable sources in the smart grid, $MVT$ and $LVT$ are respectively the sets of medium and low voltage transformers, $MC$ and $LC$ refer to the sets of medium and low consumers. $L$ is the set of electrical lines, it involves a set of principal lines $PL$ that are activated pertinently and a set of emergency lines $EL$ activated in case breakdowns and interruptions, i.e.,

$$L = PL \cup EL. \qquad (3)$$

#### 2.1.1 Failures

Smart grids can face a global list of failures $GFL(SG)$. A failure $f(x_k) \in GFL(SG)$ represents the malfunction of a component or line $x_k$ that may cause multiple propagated failures. Hence, the recorded failures list $GFL(SG)$ is categorized into «dominant» or «equivalent» that allows reducing the number of failures to be maintained and resolved as cited in (Ben Meskina et al., 2016) where we define a short fault list $SFL(SG) \subseteq GFL(SG)$, with $|SFL(SG)| \leq |GFL(SG)|$ as mentioned in Equation (4).

$$SFL(SG) = \{f(x_1), .., f(x_k), .., f(x_{N_f})\} \qquad (4)$$

where $N_f$ is the number of recorded failures in $SG$.
Let us suppose that $f(x_k) \in SFL(SG)$ is characterized by: (i) a required load $ReqL_{f(x_k)}$, (ii) a priority comparing with other failures $Pr_{f(x_k)}$, (iii) a needed recovery time $RT_{f(x_k)}$, and (iv) the waiting time without electricity $WT_{f(x_k)}$. Also, every failure $f(x_k) \in SFL(SG)$ is defined by: (i) its class in classification, (ii) a fixing time $FT_{f(x_k)}$, (iii) the proposed technical team for repairing, (iv) its waiting time for the arrival of technical team $WTA_{f(x_k)}$, (v) the recovery available time $RTA_{rs_j}$ and (vi) recovery available energy demand $E_{rs_j}$ by recovery source $rs_j$. Thereby, $SFL(SG)$ can be classified into:
(i) uncritical failures list $NCF(SG)$: includes the totally covered failures by an emergency line coming from a renewable source or central power plant, i.e.,

$$NCF(SG) = \{f(x_k) / RT_{f(x_k)} \leq RTA_{rs_j}\} \qquad (5)$$

(ii) critical failures list $CF(SG)$: contains the uncovered or insufficiently covered failures by a renewable source, i.e.,

$$CF(SG) = \{f(x_k) / RT_{f(x_k)} > RTA_{rs_j}\} \qquad (6)$$

### 2.1.2 Failures Recovery Sources

Every failure $f(x_k) \in SFL(SG)$ may have 0, 1 or $N_{EL_{f(x_k)}}$ recovery sources, in the form of electrical emergency lines coming from the power plant or existing renewable sources. We suppose that $EL_{PS}$ is the set of emergency lines coming from power plant and $EL_{RS}$ is the set of emergency lines coming from existing renewable sources, i.e.,

$$EL = EL_{PS} \cup EL_{RS} \quad (7)$$

Thus, the existing renewable sources are in the form of solar panels, wind turbines, and batteries, i.e.,

$$RS = \{pv_1, ..., pv_{N_1}, wtf_1, ..., wtf_{N_2}, bt_1, ..., bt_{N_3}\} \quad (8)$$

where $N_1$, $N_2$, and $N_3$ are respectively the existing numbers of solar panels, wind turbines, and batteries. The total recovery time $TRAT_{RS}$ and the total recovery energy $TRA_{RS}$ of the existing renewable sources in the smart grid are defined both in Equation (9).

$$\begin{cases} TRTA_{RS} = \sum_{j=1}^{N_{RS}} RTA_{rs_j} \\ TRA_{RS} = \sum_{j=1}^{N_{RS}} E_{rs_j} \end{cases} \quad (9)$$

where $N_{RS}$ is the number of renewable sources: $N_{RS} = N_1 + N_2 + N_3$, with $j = 1, .., N_{RS}$. Every proposed subset of recovery source $rs_j \subseteq RS$ is defined by: (i) the generated energy $E_{rs_j} = E_{pv} * a_1 + E_{wtf} * a_2 + E_{bt} * a_3$, and (ii) the recovery available time $RTA_{rs_j} = RT_{pv} * a_1 + RT_{wtf} * a_2 + RT_{bt} * a_3$, where $E_{pv}$, $E_{wtf}$ and $E_{bt}$ refer respectively to generated loads by a solar panel, a wind turbine or a battery. $RT_{pv}$, $RT_{wtf}$ and $RT_{bt}$ are recovery times of a solar panel, wind turbine and a battery respectively. $a_1$, $a_2$ and $a_3$ refer to the percentage of energy transformed through emergency lines to cover assigned components by $f(x_k)$. Hence, we verify the sufficiency of available energy by calculating the remaining load $Q_{k,j} = E_{rs_j} - ReqL_{f(x_k)}$.

### 2.1.3 Failures Maintenance

The maintenance phase is applied by specialized groups, working together for failures repairing, in smart grid called technical teams $TT(SG)$, i.e.,

$$\begin{cases} TT(SG) = \{TT_1, .., TT_i, .., TT_{N_{tt}}\} \\ TT(SG) = Exp(SG) \cup Tech(SG) \end{cases} \quad (10)$$

Every single technical team $TT_i \in TT(SG)$ is defined by: (i) a scheduling table $Sched_{TT_i}$, (ii) a total fixing time $TFT_{TT_i}$ and (iii) a budget $P_{TT_i}$ that defines the salary to be paid and the materials to be used during failures maintenance, with $i = 1, .., N_{tt}$ and $N_{tt}$ is the total number of teams: $N_{tt} = N_{Exp} + N_{Tech}$, where $N_{Exp}$ and $N_{Tech}$ are the numbers of expert and technician teams.

**Expert Teams** $Exp(SG)$: they are experted teams in repairing critical and hard failures with the highest priorities over components and lines in $SG$.

**Technician Teams** $Tech(SG)$: they are the teams that move to maintain medium, easy and fully recovered failures over lines in $SG$.

After defining the chosen technical team to repair a determined failure $f(x_k)$, we apply the proposed scheduling algorithm in (Ziouche et al., 2019b) to compute the total fixing time of failures for each technical team that must be equivalent or almost closest.

## 2.2 Problems

According to the existing researches on smart grids recovery enhancing, the insufficient number of technical teams that may intervene quickly to maintain failures causes a problem of: (i) long waiting time for the arrival of technical teams, and (ii) critical failures increasing due to the growth of the waiting time of clients without energy regarding covered failures with renewable energy sources, (iii) the inability of technician teams to repair some failures that need the fast intervention of an expert team, (iv) the least number of expert teams and their inability to intervene because of their occupation in other locations, and (v) the insufficiency of energy for recovery causes power and financial losses (e.g., We suppose that $f(x_k)$ is a recorded failure and it has no recovery source $RTA_{rs_j} = 0h$, it needs a recovery time from an emergency source for $RT_{f(x_k)} = 5h$. Also, the number of teams in this smart grid is $N_{tt} = 2$ where $N_{Exp} = 1$ and $N_{Tech} = 1$. The technician team tried to fix this failure, but it needs the fast intervention of an expert team with experted material while the expert team is busy in repairing another failure. In this case, $f(x_k)$ should wait for the arrival of technical team for $WTA_{f(x_k)} = 3h$, it stays without electricity for $WT_{f(x_k)} = 5h$).

## 3 CONTRIBUTION: SMART GRID RECONFIGURATION

In order to reduce the waiting time for the arrival of teams and to minimize the waiting time without electricity, we brought in Figure 1 an approach that enhances failures recovery and permits to guarantee better power availability during failures maintenance.

## 3.1 Failures Classification

The categorization of global list of failures $GFL(SG)$ into « dominant or equivalent » failures allows re-
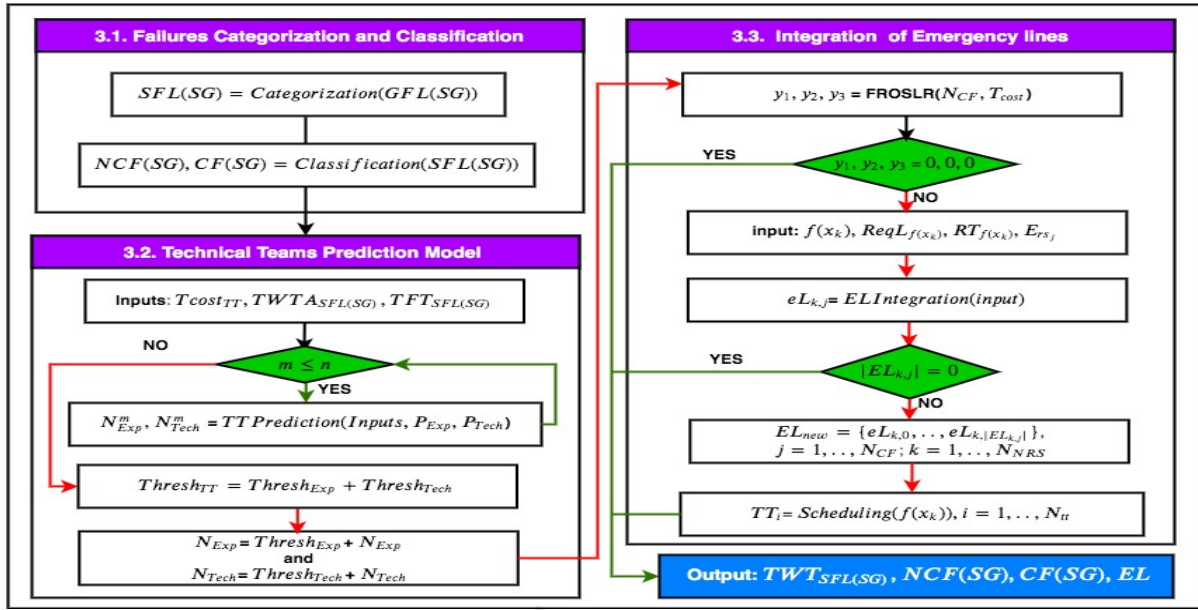
Figure 1: Smart grid Reconfiguration Architecture for availability Enhancement.

ducing the number of failures into a short fault list $SFL(SG)$. These failures are then classified into: (i) critical $CF(SG)$ and (ii) uncritical $NCF(SG)$ failures as explained in formulas (5) and (6) to determine the failures that need the fast intervention of technical teams and new recovery emergency lines.

## 3.2 Technical Teams Prediction Model

In order to realize the fast maintenance of failures, we aim to build a prediction model based on linear programming and simplex (Vaidya and Kasturiwale, 2016) that allows defining the new integrated number of technical teams according to a given budget by the electrical market. We define using equation system (11) the minimized accurate numbers of expert and technician teams.

$$\begin{cases} Minimize\ N_{tt}^m = N_{Tech}^m + N_{Exp}^m \\ N_{Tech}^m * P_{Tech} + N_{Exp}^m * P_{Exp} \leq Tcost_{TT} \\ N_{Tech}^m * TFT_{Tech} + N_{Exp}^m * TFT_{Exp} \leq \beta \\ N_{Tech}^m, N_{Exp}^m \geq 0 \end{cases} \quad (11)$$

where $N_{Tech}^m$ and $N_{Exp}^m$ refer respectively to the numbers of technician and expert teams, $P_{Tech}$ and $P_{Exp}$ refer respectively to the total salaries and used materials prices of a technician team and an expert team, $Tcost_{TT}$ is the given budget to pay new integrated technical teams. $TFT_{Tech}$ and $TFT_{Exp}$ are the total fixing times spent by a technician team and an expert team, and $\beta = TFT_{SFL(SG)}^m + TWTA_{SFL(SG)}^m$ where $TFT_{SFL(SG)}^m$ is the total fixing time of failures and $TWTA_{SFL(SG)}^m$ is the total waiting time for the arrival

of teams. Then, we adjust the constraints by adding the slack variables $e_1$ and $e_2$, i.e.,

$$\begin{cases} N_{Tech}^m * P_{Tech} + N_{Exp}^m * P_{Exp} + e_1 = Tcost_{TT} \\ N_{Tech}^m * TFT_{Tech} + N_{Exp}^m * TFT_{Exp} + e_2 = \beta \\ N_{Tech}^m, N_{Exp}^m, e_1, e_2 \geq 0 \end{cases} \quad (12)$$

This system is resolved at each month using the simplex algorithm where after a number of iterations $I$, we get the values of $N_{Tech}^m$ and $N_{Exp}^m$.

After that, we compute the accurate threshold numbers of technician and expert teams to be integrated, respectively $Thresh_{Tech}$ and $Thresh_{Exp}$, i.e.,

$$\begin{cases} Thresh_{Tech} = \frac{\sum_{m=1}^n N_{Tech}^m}{n} \\ Thresh_{Exp} = \frac{\sum_{m=1}^n N_{Exp}^m}{n} \end{cases} \quad (13)$$

where $n$ refers to the number of months that defines the historic period of study, $N_{Tech}^m$ and $N_{Exp}^m$ are the numbers of technician and expert teams at $m^{th}$ month. After getting the accurate values of thresholds, we build for each team a scheduling table.

## 3.3 Integration of Emergency Lines

To define the number of new added emergency lines into a smart grid, we take the set of critical failures $CF(SG)$ that suffer from electricity missing during blackouts, and sort them according to failure priority. We briefly indicate the set of new integrated renewable sources $NRS(SG)$ that includes respectively

Table 1: Detailed information about observed critical failures.

| $f(x_k)$ | $ReqL_{f(x_k)}$ | $RT_{f(x_k)}$ | $FT_{f(x_k)}$ | $WT_{f(x_k)}$ | $TRA_{RS}$ | $TRTA_{RS}$ | $TRA_{NRS}$ | $TRTA_{NRS}$ | $a_1 + a_2 + a_3$ |
|---|---|---|---|---|---|---|---|---|---|
| $f(L_{24})$ | 220W | 2h | 2h | 2h | 0 | 0h | 220W | 2h | 0.67+0+0 |
| $f(ML_6)$ | 2150W | 9h | 9h | 9h | 0 | 0h | - | - | - |
| $f(LVT_5)$ | 1507W | 14h | 8h | 8h | 690W | 6h | 817W | 6h | 2.12+0+0.51 |
| $f(L_{21})$ | 351W | 4h | 3h | 4h | 0 | 0h | 185W | 2h | 0.56+0+0 |
| $f(L_6)$ | 442W | 6h | 3h | 6h | 0 | 0h | 442W | 6h | 1+0.49+0 |
| $f(L_{31})$ | 262W | 4h | 4h | 4h | 0 | 0h | 262W | 4h | 0.03+0+1.21 |
| $f(L_{15})$ | 535W | 4h | 4h | 4h | 0 | 0h | 535W | 4h | 1.62+0+0 |
| $f(LVT_1)$ | 558W | 8h | 5h | 2h | 400W | 6h | 158W | 2h | 0+0+0.79 |

$y_1$ solar panels, $y_2$ wind turbines and $y_3$ batteries as reported in (Ziouche et al., 2019a). In order to maximize the number of added emergency lines coming from renewable sources that satisfy the required load of $f(x_k)$ and cover it during the intervention of technical teams, we certify the following constraints, i.e.,

$$\begin{cases} Maximize\ N_{EL_{f(x_k)}} = a_1 + a_2 + a_3 \\ a_1 + a_2 + a_3 \leq N_{NRS} \\ E_{pv} * a_1 + E_{wtf} * a_2 + E_{bt} * a_3 \geq ReqL_{f(x_k)} \\ RT_{pv} * a_1 + RT_{wtf} * a_2 + RT_{bt} * a_3 \geq \alpha \\ a_1, a_2, a_3 \geq 0 \end{cases}$$
(14)

where $\alpha = WTA_{f(x_k)} + FT_{f(x_k)}$ is the needed time for coverage by renewable sources.

To adjust the proposed constraints, we add the three slack variables respectively $e_1$, $e_2$ and $e_3$, i.e.,

$$\begin{cases} a_1 + a_2 + a_3 + e_1 = N_{NRS} \\ E_{pv} * a_1 + E_{wtf} * a_2 + E_{bt} * a_3 - e_2 = ReqL_{f(x_k)} \\ RT_{pv} * a_1 + RT_{wtf} * a_2 + RT_{bt} * a_3 - e_3 = \alpha \\ a_1, a_2, a_3, e_1, e_2, e_3 \geq 0 \end{cases}$$
(15)

We apply simplex algorithm to resolve the equation systems. We re-compute the remaining numbers of $y_1$, $y_2$, $y_3$ and the remaining total available load of new renewable sources $TRA_{NRS}$ of the existing failure in the critical failures list. The used percentage of energy load from a new renewable source indicates adding a new emergency line going from the defined source to its final destination. Finally, we can build the new set of added emergency lines $EL_{new} = \{eL_{k,j}/Q_{k,j} \geq 0\}$ with $eL_{k,j}$ is the new emergency line that connects the $k^{th}$ failure and $j^{th}$ integrated renewable source.

Then, we apply the scheduling algorithm proposed in (Ziouche et al., 2019b) to build final scheduling tables, and we re-define the value of $TWT_{SFL(SG)}$ and the critical $CF(SG)$, uncritical failures $NCF(SG)$.

# 4 IMPLEMENTATION & RESULTS

In order to evaluate the proposed prediction model, we have implemented a tool called SGREP that is applied to a real case study. Then, we have validated the obtained gains through real-time experimental study.

## 4.1 Case Study

The proposed contribution is demonstrated and illustrated through the following real-time study. We consider the real meshed power network -North Urban Center $SG$ (Tunis, Tunisia)- as presented in Figure 2.
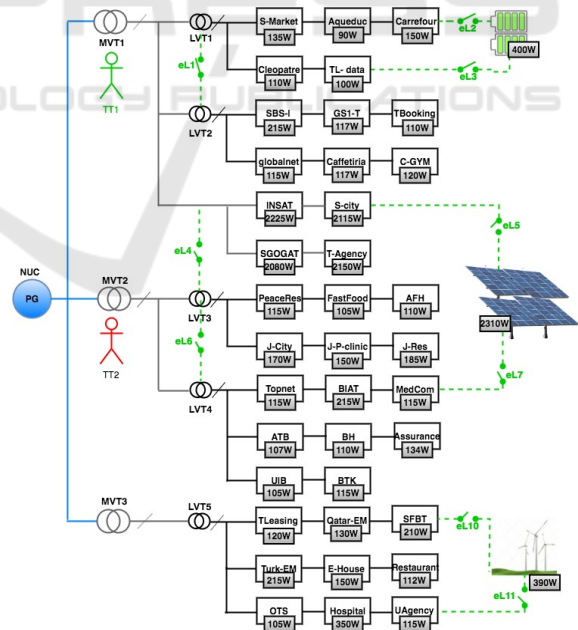


Figure 2: Case study on North Urban center smart grid.

$SG$ is composed of a power generator $PG$, eight transformers: 3 $MVT$ and 5 $LVT$, thirty-eight consumers: 4 $MC$ and 34 $LC$, with nine emergency lines $EL$: 3 $EL_{PS}$ and 6 $EL_{RS}$. We assume that there are two technical teams that intervene to repair failures in

$SG$ ($N_{Exp} = 1$ and $N_{Tech} = 1$). $SG$ is supervised and controlled through smart agents and devices that detect and isolate malfunctioned lines as explained in (Ben Meskina et al., 2016).

Table 2: Observed values of studied smart grid.

| Month | Jan | Feb | Mar | Apr | May | Jun |
|---|---|---|---|---|---|---|
| $N_f$ | 15 | 9 | 13 | 14 | 12 | 10 |
| $N_{CF}$ | 8 | 4 | 7 | 8 | 6 | 5 |
| $TReqL_{CF}$ | 6.03 | 2.65 | 5 | 5.02 | 2.29 | 4.06 |
| $TWT_{CF}$ | 39h | 21h | 30h | 14h | 21h | 25h |
| $TFT_{CF}$ | 53h | 38h | 41h | 50h | 32h | 40h |
| $TRTA_{RS}$ | 12h | 12h | 6h | 0h | 0h | 10h |

After a deep supervision of six successive months, we consider (i) the number of recorded failures $N_f$, (ii) the number of critical failures $N_{CF}$, (iii) the total required load (in kilowatts), (iv) total fixing time (hours), (v) total waiting time (hours), and (vi) the total available recovery time as shown in Table 2 (e.g., In January, the recorded number of critical failures is $N_{CF} = 8$. These last need a total required load of $TReqL_{CF} = 6.03kWh$. Technical teams spend $TFT_{SFL(SG)} = 53h$ to fix these failures where the initial total waiting time without energy is $TWT_{SFL(SG)} = 39h$). Thereby, we suppose that the given budget by the electricity market to integrate a new number of renewable sources in $SG$ is $T_{cost} = 6000\$$. The given budget to pay the newly added number of technical teams is $Tcost_{TT} = 3000\$$ and the paid salaries to a technician and an expert team are in order: $P_{Exp} = 1200\$$, $P_{Tech} = 770\$$. Also, we suppose that the quantity of generated energy by a solar panel, a wind turbine, and a battery are successively: $E_{pv} = 330W$, $E_{wtf} = 230W$ and $E_{bt} = 200W$, the prices of a solar panel, a wind turbine and a battery are respectively: $P_{pv} = 710\$$, $P_{wtf} = 600\$$, $P_{bt} = 450\$$, and the recovery times available by a solar panel, a wind turbine and a battery are in order: $RT_{pv} = 3h$, $RT_{wtf} = 2h$ and $RT_{bt} = 3h$.

**Step 1: Failures Classification.** Let us suppose that $SFL(SG)$ includes fifteen failures, we use the formulas (5) and (6) to classify failures into:
$CF(SG) = \{f(L_{24}), f(L_{21}), f(ML_6), f(LVT_1), f(L_6),$
$f(L_{31}), f(LVT_5), f(L_{15})\}$, $NCF(SG) = \{f(LVT_3),$
$f(ML_1), f(ML_2), f(L_{19}), f(L_{24}), f(L_4), f(L_{38})\}$. The proposed scheduling tables allow computing the total waiting times without electricity and for the arrival of technical teams respectively: $TWT_{CF} = 39h$ and $TWTA_{SFL(SG)} = 115h$.

**Step 2: Technical Teams Prediction Model.** The growth total waiting time without electricity of recorded failures and total fixing time of failures show that the existing two technical teams for failures maintenance in $SG$ are insufficient. Thus, we apply the proposed prediction model in Section 3.2 on January to define the minimum number of teams to be integrated into $SG$. Based on the proposed linear programming system in formulas (11) and (12), we compute using simplex algorithm the accurate values of expert and technician teams. We find: $N_{Exp} = 1$ and $N_{Tech} = 2$. We re-apply the same process on the five remaining months to predict the accurate thresholds of expert and technician teams with the help of formula (13), we find: $Thresh_{Exp} = 1$, and $Thresh_{Tech} = 2$. The total numbers of technician and expert teams are respectively $N_{Tech} = 3$ and $N_{Exp} = 2$.

**Step 3: Integration of Emergency Lines.** Based on the implemented tool FROSLR in (Ziouche et al., 2019a), we can predict the accurate threshold of integrated renewable sources $Thresh_{NRS} = 9$ with the accurate values of added solar panels $y_1 = 6$, wind turbines $y_2 = 1$ and batteries $y_3 = 2$. The total recovery time available $TRTA_{NRS} = 26h$ and total available energy for recovery $TRA_{NRS} = 2610W$. Then, we compute the maximized number of emergency lines using formulas (14) and (15) and simplex algorithm.

Table 1 illustrates the detailed information of critical failures recovery after integrating a new number of renewable sources in January month (e.g., A failure occurred on $LVT_1$ requires a load of $558W$ for $8h$. Technical teams must spend $5h$ to fix this failure, the clients of this region wait without electricity for $2h$, it is covered through available renewable sources for $6h$ and after adding one emergency line coming from a battery $N_{EL_{new}}(f(LVT_5)) = 1$, where $TRA_{NRS} = 158W$ and $TRTA_{NRS} = 2h$). Hence, the application of the proposed reconfiguring strategy is applied in the same way on the five rest months to determine the numbers of critical and uncritical failures and emergency lines. They are respectively equal to $N_{NCF} = 13$, $N_{CF} = 2$ and $N_{EL_{new}} = 13$.

The system applies a scheduling algorithm to assign priorities and teams to all existing failures. We get at the end five scheduling tables where the total fixing times are almost equal. The obtained scheduling tables are: $Sched_{Exp_1} = \{f(ML_6), f(LVT_3), f(L_1)\}$
$Sched_{Exp_2} = \{f(LVT_5), f(ML_2), f(L_{19})\}$
$Sched_{Tech_1} = \{f(L_{24}), f(L_{31}), f(LVT_3), f(L_4)\}$
$Sched_{Tech_2} = \{f(L_{21}), f(LVT_1), f(ML_1)\}$
$Sched_{Tech_3} = \{f(L_6), f(L_{15}), f(L_{38})\}$
Hence, we get: $TWT_{CF} = 11h$ and $TWTA_{CF} = 5h$.

## 4.2 Performance Evaluation

To illustrate the obtained gains using simulated tool SGREP, we define for every smart grid $SG$ two metrics that are the total availability rate and the total

Table 3: The structure of investigated smart grids.

| $SG$ | $|CONS|$ | $N_f$ | $|EL|$ | $TReqL_{CF}$ | $N_{RF}$ | $N_{NRF}$ | $N_{RS}$ | $\sigma_{init}(SG)$ | $\sigma_{RB}(SG)$ | $\sigma_{Froslr}(SG)$ |
|------|----------|-------|--------|--------------|----------|-----------|----------|---------------------|-------------------|------------------------|
| $SG_1$ | $34LC+4MC$ | 38 | 12 | 2.06 kWh | 16 | 18 | 3 | 47.06% | 70.58% | 85.29% |
| $SG_2$ | $75LC+8MC$ | 83 | 25 | 4.25 kWh | 41 | 42 | 5 | 49.36% | 71.08% | 79.51% |
| $SG_3$ | $122LC+28MC$ | 150 | 54 | 5.67 kWh | 78 | 72 | 7 | 52% | 71.33% | 78% |
| $SG_4$ | $142LC+38MC$ | 180 | 65 | 6.87 kWh | 98 | 62 | 10 | 54.44% | 72.78% | 81.11% |

waiting time rate.

### 4.2.1 Total Availability Rate

-Denoted by $\sigma_{SG}$-, it represents the rate of the total number of covered failures thanks to the proposed reconfiguration for integrating a new number of technical teams and emergency lines, i.e.,

$$\sigma_{SG} = \frac{N_{RF}}{N_f} \qquad (16)$$

where $N_{RF}$ is the number of recovered failures.

### 4.2.2 Total Waiting Time Rate

-Denoted by $\rho_{SG}$-, it refers to the rate between the initial and final total waiting time before and after applying the new reconfiguring strategy, i.e.,

$$\rho_{SG} = \frac{TWT_{END}(SFL(SG))}{TWT_{init}(SFL(SG))} \qquad (17)$$

where $TWT_{init}(SFL(SG))$ refers to the initial total waiting time and $TWT_{END}(SFL(SG))$ refers to the waiting time after applying the new heuristic.
In case study, we have $\sigma_{SG} = 80\%$ and $\rho_{SG} = 47\%$.
In order to reduce the number of non-recovered failures through smart grids, an experimental study is applied to four real meshed power networks of the Tunisian power systems cited in (Ziouche et al., 2019b). They have different sizes: $SG_1$ and $SG_2$ are two small smart grids, $SG_3$ is a medium one, and $SG_4$ is large. They include different numbers of electrical components and lines, the structure of this power grids is investigated completely in Table 3 by defining (i) the number of consumers $|CONS|$, (ii) the number of existing emergency lines $|EL|$, (iii) the number of recorded failures $N_f$, (iv) the total required load of critical failures $TReqL_{CF}$, (v) $N_{RF}$ is the number of recovered failures, (vi) $N_{NRF}$ is the number of non-recovered failures, and (vii) $N_{RS}$ is the number of available renewable sources in the smart grid (e.g., $SG_2$ is a small smart grid, it includes 83 consumers, the number of recovered consumers in smart grid is about 41 and non-recovered is 42, and the number of existing renewable sources is 5).

Table 4: The structure of simulated smart grids by SGREP.

| $SG$ | $|EL_{new}|$ | $N_{tt}$ | $N_{NRS}$ | $N_{RF}$ | $\sigma_{SGREP}(SG)$ |
|------|--------------|----------|-----------|----------|----------------------|
| $SG_1$ | 13 | 5 | 9 | 28 | 87.8% |
| $SG_2$ | 20 | 7 | 12 | 61 | 81.49% |
| $SG_3$ | 28 | 10 | 18 | 110 | 83.33% |
| $SG_4$ | 36 | 12 | 21 | 135 | 85% |

Table 4 represents the structure of simulated smart grids using the software tool SGREP, we define (i) the new number of emergency lines $|EL_{new}|$, (ii) the predicted number of technical teams $N_{tt}$, (iii) the new number of recovered failures $N_{RF}$, and (iv) the integrated number of renewable sources through FROSLR $N_{NRS}$. The addition of emergency lines and technical teams allow to enhance the power availability rate (e.g., $SG_2$ needs a total required load of 4.25 $kWh$, where the number of new added renewable sources is 12, it permits to integrate 20 renewable sources and 7 technical teams: $N_{Tech} = 4$ and $N_{Exp} = 3$. Thanks to proposed reconfiguration, we remark an increasing in term of total availability rate from 85.29% to 87.8%, besides a reduction in the term of waiting time to 48%).
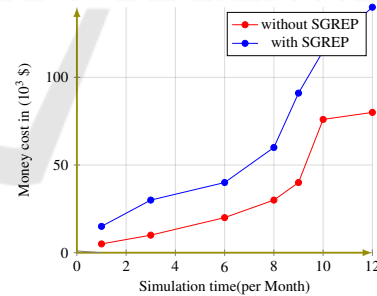


Figure 3: Financial gains due to SGREP simulator.

Moreover, The prediction of the number of technical teams increases the number of fixed failures. Figure 3 shows a comparative study in term of the financial cost before and after applying the reconfiguration. We identify a remarked increasing to more than $135 * 10^3$\$ per year. Figure 4a represents the cumulative waiting time of clients during the intervention of technical teams, it reports a comparison of the waiting times using SGCS-RB, FROSLR and SGREP. Thereby, we supervise a remarked reduction in the term of waiting time. Figure 4b compares the growth in term of the total availability of energy dur-
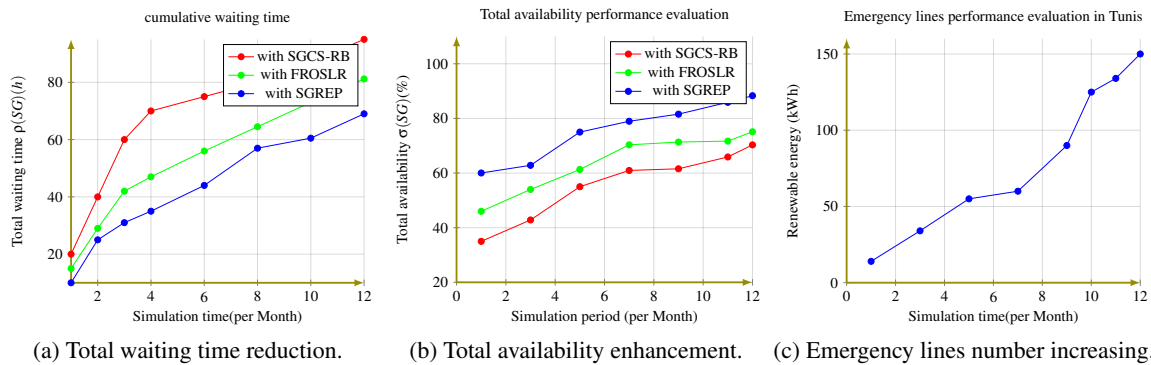
Figure 4: Performance Evaluation due to Reconfiguring Simulator SGREP.

ing failures recovery in $SG_1$ after applying different contributions. Thus, the addition of the new number of emergency lines coming from added renewable sources allows for increasing the recovery of failures. Figure 4c shows the annual increase of use of renewable sources by integrating a new number of emergency lines that allow to better enhance the recovery of the power network. So that, the implemented simulator SGREP helps electricity markets to satisfy the recovery and maintenance of recorded critical failures and encourages the use of renewable sources.

Furthermore, SGREP permits to improve the performed rates in term of power availability and total waiting time thanks to implemented prediction model.

# 5 CONCLUSIONS

To guarantee the accurate integrated numbers of technical teams and emergency lines for best improvement of failures recovery and maintenance in smart grids, we have proposed a reconfiguration approach that permits to predict the integrated number of expert and technician teams, besides the addition of a new number of emergency lines which allows increasing the total availability of energy during interruptions and outages of more than 2% with the reduction of total waiting time without energy to the half. This approach permits to reduce economic losses during blackouts. In the future work, we aim to secure transmitted data in the smart grid proposed architecture, beside verifying formally the proposed strategies.

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