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ASSESSING EARTHQUAKE DAMAGE FOR GAS DISTRIBUTION NETWORKS: UNCERTAINTY ANALYSIS APPLICATION IN TLEMCEN (ALGERIA)

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ABSTRACT: It is currently admitted that Repair Rate per kilometer (RR) is one of the most suitable tools to measure the fragility of lifeline structures after earthquake. Many models have been developed during last decades and use seismic parameters. These later are derived from ground motion prediction equations (GMPE). Most of the above mentioned models do not take into account the inherent variability of the GMPE. This paper aims to establish a methodology to derive the repair rate by taking account the variability associated with the GMPE. Through this methodology average as well as weighted average repair rates will be established. In order to apply the developed methodology, a model based on Peak ground velocity (PGV) is chosen. Through a sensitive case study it has been found that the weighted average repair rate is the most suitable. Indeed the obtained results show that the proposed approach leads to stable values of the repair rate whereas values obtained from other methods are not stable. Finally, weighted average values of RR obtained from the developed methodology are compared to conventional values obtained for a single GMPE and without uncertainty at the level of urban area (District of Tlemcen, Algeria). This comparative study shows that the developed methodology leads to interesting results.

Keywords: Buried Pipeline, Peak Ground Velocity (PGV), Repair Rate (RR), Ground Motion Prediction Equation (GMPE).

1. INTRODUCTION

Repair Rate per kilometer (RR) is one of the most suitable tools to measure the fragility of lifeline structures after earthquake. Seismic analysis of the buried pipelines is important since the number of the required information used is very important. Indeed engineers needs to know which soil types and seismic actions are be used in the analysis. This will certainly avoid the total collapse of the lifeline and reduce the risk of explosion that will affect the entire network [1].

RR use seismic parameters which in turn are derived from numerous approaches described by attenuation relationship also known as GMPE (Ground Motion Prediction Equation).This later have great variability which was extensively studied and assessed in numerous recent papers, such as the NGA [2], NGAW2 [3] and RESORCE [4] studies.

In this paper we propose a methodology that takes into account the inherent variability of the ground motion parameters. Through this methodology we try to understand how this variability will shape the form of the repair rate. This methodology will be developed considering a particular relationship between a Ground Motion Parameters (*GMP*) and RR, a number of GMPE that provide GMP and their associated variability. We then attempt to capture the effect of the inherent variability of GMPE on RR. In order to apply the developed methodology, a model based on Peak ground velocity (PGV) is chosen [5]. It worth noting that the developed methodology could be applied for other models that used other seismic parameters like for instance on the peak ground acceleration (PGA).

The newly developed approach leads to the establishment of weighted average repair rate instead of unique repair rate.

These weighted average values of RR are then compared to conventional values obtained for a single GMPE and without uncertainty.

2. METHODOLOGY

The repair rate (RR) is currently admitted as one of the most used tools to describe the fragility of lifeline structures. It is established through correlations between the observed number repairs per kilometer and the associated ground motion parameters (GMP) which could be either Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement (PGD) and other.

$$\boldsymbol{RR} = \boldsymbol{RR}_{(\boldsymbol{GMP})} = \boldsymbol{f}(\boldsymbol{GMP}) \quad (1)$$

For instance the model proposed in ALA database [5] gives RR knowing the value of PGV. This model is provided in Eq (2).

$$\boldsymbol{RR = b.PGV^{C}} \quad (2)$$

Where b=0.00108, c=1.173 and PGV is given in inch/s.

The above relationships doesn't mention a standard deviation (noted as σ_{RR}), it is obvious that there exists a huge uncertainty in the estimation of the repair rate.

Thus it is important to assess σ_{RR}.

The PGV is derived from GMPE, we use seismological and site parameters to estimate it.

Let assume that we have n available GMPE (noted GMPEi, i=1,...,n).

Each particular GMPE model#i will provide an estimate of GMP_i . Obviously for the same seismological and site parameters and using the same relationship Eq. (1), two models of GMPE will give different values of repair rate: $RR_{(GMP_i)}$.

Thus the n available GMPE will provide n values of repair rate ($RR_{(GMP_i)}, i = 1..n$). The following part will give us an overall idea on the 'best estimate' of the repair rate.

Let compute the mean value of the n values ($GMP_i, i = 1..n$):

$$\boldsymbol{\overline{GMP} = \frac{1}{n}\sum\nolimits_{i=1}^{n} GMP_i} \quad (3)$$

Then $RR^{(1)}$ is calculated as follow:

$$\boldsymbol{RR^{(1)} = RR_{(\overline{GMP})}} \quad (4)$$

This method is named method#1

Let compute the mean value of $RR_{(GMP_i)}$ from the n GMPi. This value will be referred in the following as $RR^{(2)}$ and named method #2.

$$\boldsymbol{RR^{(2)} = \frac{1}{n}\sum\nolimits_{i=1}^{n} RR_{(GMP_i)}} \quad (5)$$

Both methods do not take into account the variability of each GMPE models. The two other methods consider the variability's of the used GMP (through σ_{GMP}) and the resulting estimation of σ_{RR} , except that it will be a bit complex; for the first one is fairly well known for "classical" GMP such as PGV for our case. The second one (σ_{RR}) is never given.If we consider each GMPE with its standard deviation the mean value of the GMP is defined by a particular GMPE model#i.

$$\mathbf{\log(\overline{PGV_i}) = \log(PGV_i) \pm \sigma_{\log(PGV_i)}} \quad (6)$$

From this later we can evaluate the impact of the GMPE model#i variability on the $RR_{(PGV_i)}$ estimates. In addition of PGV_i we have also $PGV_i * 10^{\sigma_{\log(PGV_i)}}$ and $PGV_i * 10^{-\sigma_{\log(PGV_i)}}$.

We then obtain three value of repair rate:

$\mathbf{RR_{(PGV_i)} = RR_{(V_{i2})}}$,

$\mathbf{RR_{\left(PGV_i * 10^{\sigma_{\log(PGV_i)}}\right)} = RR_{(V_{i1})}}$

$\mathbf{RR_{\left(PGV_i * 10^{-\sigma_{\log(PGV_i)}}\right)} = RR_{(V_{i3})}}$

Table 1. Derivation of RR_{ijk} $j, k = 1,2,3$.

		$RR_{i11} = RR_{V_{i1}} + \sigma_{RR}$
	$V_{i1} = PGV_i * 10^{\sigma_{\log(PGV_i)}}$	$RR_{i12} = RR_{V_{i1}}$
		$RR_{i13} = RR_{V_{i1}} - \sigma_{RR}$
		$RR_{i21} = RR_{V_{i2}} + \sigma_{RR}$
$V_i = PGV$	$V_{i2} = PGV_i$	$RR_{i22} = RR_{V_{i2}}$
		$RR_{i23} = RR_{V_{i2}} - \sigma_{RR}$
		$RR_{i31} = RR_{V_{i3}} + \sigma_{RR}$
	$V_{i3} = PGV_i * 10^{-\sigma_{\log(PGV_i)}}$	$RR_{i32} = RR_{V_{i3}}$
		$\boldsymbol{RR_{i33} = RR_{i13} - \sigma_{RR}}$

We also take into account the uncertainty in the RR estimate , if σ_{RR} is available, so for each given GMPE model # i we obtain RR, RR - σ_{RR} and RR + σ_{RR}. Thus for a single GMPE model we have nine estimates of repair rate (Table 1), so for n GMPE we will have L repair rate where: L=9*n (Fig.1)

Noted as RR_{ijk} where $(i = 1 \dots n)$, $(j = 1 \dots 3)$, $(k = 1 \dots 3)$.

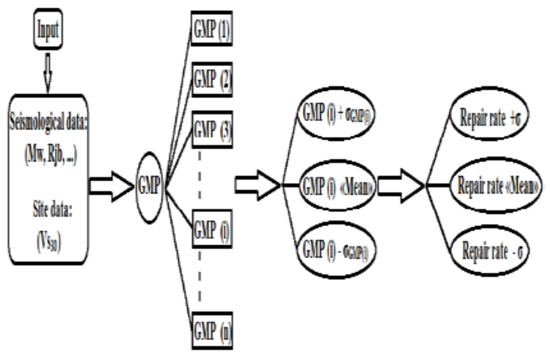


Fig. 1 Flow chart for RR estimation accounting for some level of epistemic uncertainty.

We can then compute the averaged RR as:

$$RR^{(3)} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{3}\sum_{k=1}^{3} RR_{ijk}}{9n} \quad (7)$$

This method is named method#3.

This method take into account the inherent variability of the GMPE models, but not the degree of confidence of the GMPE model. For the method#4 we introduce weighting factors W_{ijk} to be applied to each estimateRR_{ijk}:

$W_{ijk} = \omega_i \mu_j \vartheta_k$ (8)

ω_i ($i = 1 \dots n$) depend on the weight of GMPE.

Assigning such weights usually relies on expert opinion [6] or alternatively on the value of σ_{GMP}, with the lowest variability being assigned the highest weight. μ_j ($j = 1 \dots 3$) defined as a weight of different expected probabilities for the considered estimates of GMP .Similarly, ϑ_k($k = 1 \dots 3$) is introduced as a weight to take into account the uncertainty in RR estimates.

$RR^{(4)} = \sum_{i=1}^{n} \sum_{j=1}^{3} \sum_{k}^{3} W_{ijk} RR_{ijk}$ (9)

Where $W_{ijk} RR_{ijk} = L_{ijk}$.

This method is named method#4.

So we have 4 methods to estimate RR: $RR^{(m)}, m = 1,..,4$; then it is necessary to measure the degree of confidence of the fourth values. For $RR^{(1)}$, as there is only one value then the standard deviation is $\Delta^{(1)} = 0$. Regarding $RR^{(l)}$ $l = 2,3,4$ the standard deviation will be measured as follow:

$$\Delta^{(2)} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \sigma_{GMP} \left(RR_{(GMP_i)} - RR^{(2)}\right)^2} \quad (10)$$

$$\Delta^{(3)} = \sqrt{\frac{1}{9n} \sum_{i=1}^{n} \sum_{j=1}^{3} \sum_{k}^{3} \sigma_{GMP_i} \left(RR_{ijk} - RR^{(3)}\right)^2} \quad (11)$$

$$\Delta^{(4)} = \sqrt{\frac{1}{9n} \sum_{i=1}^{n} \sum_{j=1}^{3} \sum_{k}^{3} \sigma_{GMP_i} W_{ijk} \left(RR_{ijk} - RR^{(4)}\right)} \quad (12)$$

3. INPUT USED IN THE CURRENT STUDY

3.1 General statement

Among the proposed parameters for assessment of the buried pipelines we choose the peak ground velocity (PGV) [7]. The number of GMPE used herein is three, thus $n = 3$. After describing the GMPE models that will be used in this paper, we will present how we derive the inherent variability associated with RR.

3.2 Model of Akkar & Bommer (2010)

The GMPE established by [7] provides the 5%-damped pseudo-spectral acceleration; it will be reported as model#1. The PGV, in units of cm/s through the following generic equation:

$$\log(PGV) = b_1 + b_2 M + b_3 M^2 + (b_4 + b_5 M) \log\sqrt{{R_{jb}}^2 + {b_6}^2} + b_7 S_S + b_8 S_A + b_9 F_N + b_{10} F_R + \varepsilon\sigma \quad (13)$$

Where: M is the moment magnitude, R_{jb} is the epicentral distance, S_S and S_A are introduced to describe site effects and depend on the value of VS30. F_N and F_R are introduced to describe fault type. The constants b_i, $i = 1,2,..10$ and $\sigma_{\log(PGV)} \equiv \sigma = \sqrt{\sigma_1^2 + \sigma_2^2}$ provided in Table 2. $\sigma_{\log(PGV)} = 0.2781$.

Table 2. Values of the GMPE coefficients for PGV.

b_1	b_2	b_3	b_4	b_5
-2.1283	1.2144	-0.0813	2.4694	0.2234
b_6	b_7	b_8	b_9	b_{10}
6.4144	0.2035	0.0848	-0.0585	0.0130

σ_1	σ_2
0.256	0.108

3.3 Model of Derras (2014)

This model is based on the artificial neural network approach presented in [8], and on the European RESORCE data set, referred as model#2. This RESORCE data set consists of 1088 recordings from 320 earthquakes covering source-to-site distances up to 547 km and a magnitude range from 3.6 to 7.6. The input parameters are Mw, Rjb, Depth (D) and focal mechanism (FM), and a continuous site condition proxy (Vs30). The standard deviation of this model is $\sigma_{\log(PGV)} = 0.298$.

3.4 Sabetta & Pugliese (1996)

Fabio Sabetta and Antonio Pugliese, 1996, proposed a GMPE as follow [10]:

$$Log_{10}(PGV) = a + b.M + c.Log_{10}(R^2 + h^2)^{1/2} + e_1.S_1 + e_2.S_2 \pm \sigma \quad (14)$$

M is the moment magnitude; R is the epicentral or fault distance (Km), S_1 and S_2 dummy vari able for the site class (shallow, deep and stiff soil). For the constant and the standard deviation refer toTable 3.

Table 3. Values of the GMPE coefficients for PGV.

a	b	c	
-0.710	0.455	-1	
e_1	e_2	h	σ
0.133	0.133	3.6	0.215

Through the extent of GMPE available in the literature, we could choose more GMPE, except that the number of proposed model is sufficient to achieve the objective of this paper.

Regarding the variability of the mean of value of PGV for the above models, we found that for a particular scenario: $M = 6.5$, soft soil, depth=10 Km and normal fault, values of PGV exhibit great difference (Fig. 2) even if we have imposed a unique set of seismological parameters and site conditions.

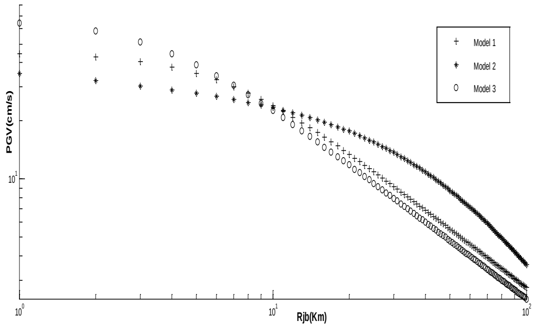


Fig. 2 Comparison of the 3 different models of the estimation of PGV
Model 1: AKKAR and al.
Model 2: DERRAS and al.
Model 3: SABETTA and al.

3.5 Derivation of σ_{RR}

We compare between observations and predictions of RR. We use here the database of observed RR provided in [5]. This database contains several records of RR, we note RR_{obs} to compare with RR_{pre} through Eq. (2) and the corresponding values of the GMP's. Only 46 observation points mentioned above gives RR_{obs} and GMP's in terms of PGV. Fig. 3 displays the variation of RR_{pre} with RR_{obs} .

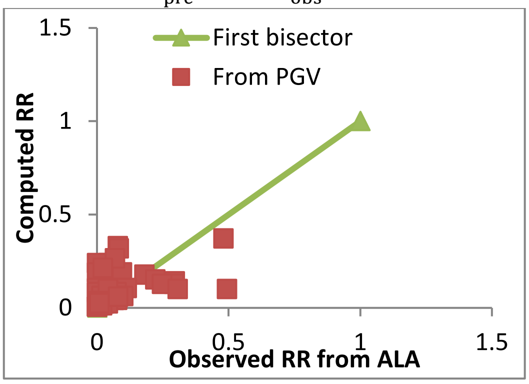


Fig. 3 Comparison between the predicted RR and the observed one for the ALA data set.

For that :

$$\sigma_{RR} = \sqrt{\frac{1}{N_{Obs}} \sum_{I=1}^{46} \left(RR_I^{Obs} - RR_I^{Pre}\right)^2} = 0.04 \qquad (15)$$

This value shows the total variability of RR, which is indeed very significant. Also Fig. 3 depicts the variation of the predicted repair rate versus the measured one.

4. RESULTS

4.1 Weighted mean estimate

In this section the developed methodology together with input provided in previous section will be used to compute the repair rate defined in the second section.We give the largest weight to the model with the lowest variability, and the lowest weight to the largest variability model:

$$\sigma_{\log(PGV)} = \begin{cases} 0.278 \\ 0.298, \\ 0.215 \end{cases} \quad \text{thus} \quad \begin{cases} \omega_1 = 0.3 \\ \omega_2 = 0.3 \\ \omega_3 = 0.4 \end{cases} \qquad (16)$$

About the three branches associated with the median and median ± one standard deviation, they were assigned weights of 0.6 and 0.2, respectively, so that:

$$\begin{cases} \mu_1 = 0.2 \\ \mu_2 = 0.6 \\ \mu_3 = 0.2 \end{cases}, \quad \begin{cases} \vartheta_1 = 0.2 \\ \vartheta_2 = 0.6 \\ \vartheta_3 = 0.2 \end{cases} \qquad (17)$$

4.2 Examples study

Case study 1

We take a case for a soft soil with: M = 6.5, soft soil (VS30= 200 m/s), depth=10 Km, R_{jb} = 10 Km and normal fault. The nine values per model are then computed according to the general schemes (see Table 1). Fig 4 gives the variation of these values for the three models. The fifth case represents of the repair rate without taking into account the variability of the GMPE. It is obvious that neglecting variability could underestimate RR.

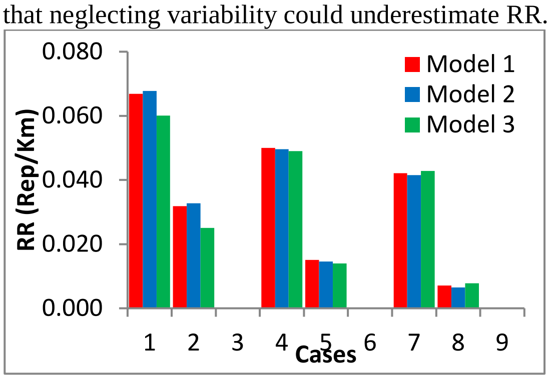


Fig.4 Values obtained along the 27 values of RR. Case study 1

As mentioned in section two, $RR^{(m)}$ m = 1,..,4 are then computed.

Method#1:

$$\overline{PGV} = \frac{9.223+9.446+8.896}{3} = 9.188\ \text{inch/s} \qquad (18)$$

The corresponding RR estimate according to RR relationship Eq. (2) is thus

$$RR^{(1)} = 0{,}0485 \qquad (19)$$

Method#2:

$$RR^{(2)} = \frac{0.0467+0.0501+0.0487}{3} = 0{,}0486 \qquad (20)$$

Method#3 and method#4 take into account the variability related to both PGV and RR prediction equations, through the computation of the RR_{ijk} values as described in previous section. We found that:

$$RR^{(3)} = 0{,}0771 \quad (21)$$

$$RR^{(4)} = 0{,}0661 \quad (22)$$

Case study 2

We repeated the same approach considering know a stiff site located at the same distance and the same earthquake scenario considered in case study 1.

The resulting mean value of PGV and the $RR^{(m)}$ m = 1,..,4 estimates can be derived in a similar way:

$$\overline{PGV} = \frac{6.549 + 5.911 + 5.352}{3} = 5.937 \text{ inch/s} \quad (23)$$

Leading to the following RR(1) estimate

$$RR^{(1)} = 0.0291 \quad (24)$$

$$RR^{(2)} = \frac{0.0326+0.0289+0.0257}{3} = 0.0291 \quad (25)$$

Fig. (5) gives the distribution of RR_{ijk}.

$$RR^{(3)} = 0.0617 \quad (26)$$

$$RR^{(4)} = 0.0493 \quad (27)$$

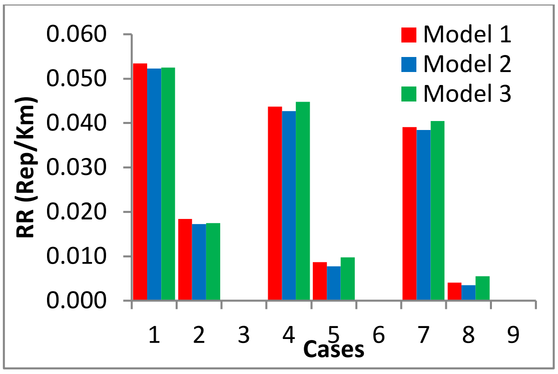


Fig.5 Values obtained along the 27 values of RR. Case study 2

4.3 Comprehensive comparison between RR(m) estimates

The previous estimating repair rate for both types of soils, mentioned in Eqs. (19)-(22) and (24)-(27) can be ranked as follows.

For soft soil:

$$RR^{(1)} < RR^{(2)} < RR^{(4)} < RR^{(3)} \quad (28)$$

For stiff soil:

$$RR^{(1)} = RR^{(2)} < RR^{(4)} < RR^{(3)} \quad (29)$$

Estimating $RR^{(4)}$ for soft and stiff soil cases remains in the middle position, whereas $RR^{(1)}$, $RR^{(2)}$ and $RR^{(3)}$ can be lowest or highest. That result suggests that weighted average is more accurate than the other.

We measured the degree of confidence of the fourth value through standard deviation (Eqs. (10)-(12)). Results obtained (Eqs (30)-(31)) show that the method#4 model has intermediate value of standard values.

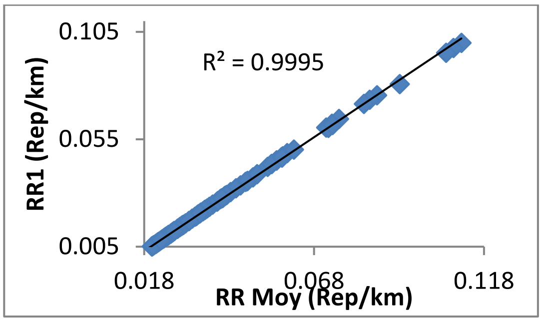
For soft soil:

$$\Delta^{(3)} < \Delta^{(4)} < \Delta^{(2)} \quad (30)$$

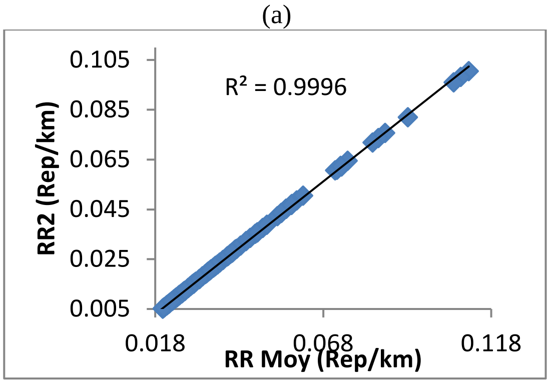
For stiff soil:

$$\Delta^{(3)} < \Delta^{(4)} < \Delta^{(2)} \quad (31)$$

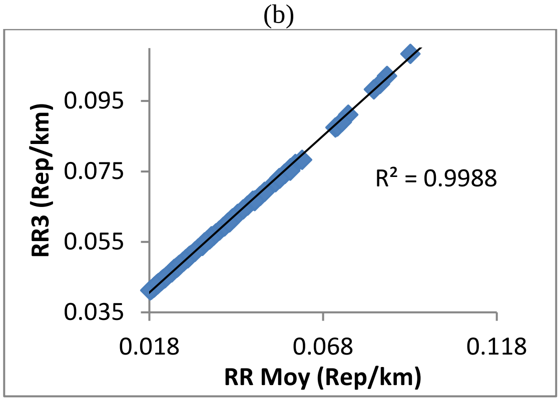
In order to generalize the result obtained from the previous case studies, we compared $RR^{(m)}$ and $\Delta^{(m)}$ for larger number of cases. We have considered a total of 125 cases corresponding to 5 different magnitudes (5, 5.5, 6.0, 6.5 and 6.8), different Rjb distances (5, 10, 15, 25, and 50 km), and 5 different Vs30 values (200, 250, 300, 500 and 750 m/s) and compared with the mean of the 4 estimates. The overall results displayed in Fig. 6 for the 125 cases indicate that the method providing the closest estimate to the mean one is the method # 4.



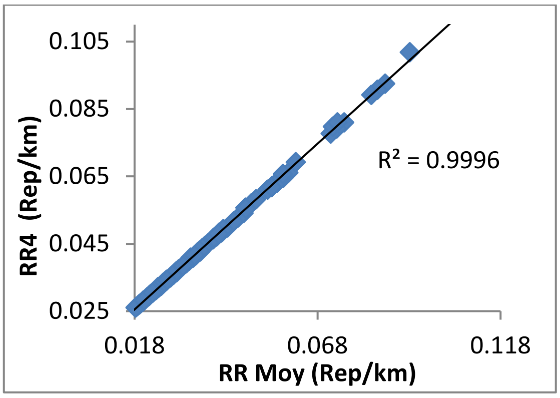
(a)



(b)



(c)



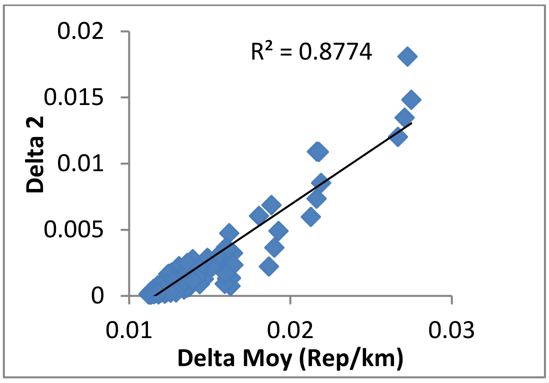
(d)

Fig. 6 Summary comparison for the 125 cases between the different of RR for each method [the corresponding estimate are plotted as a function of the mean estimate derived from the 4 models].
(a)Method 1; (b)Method 2; (c)Method 3; (d)Method 4 .

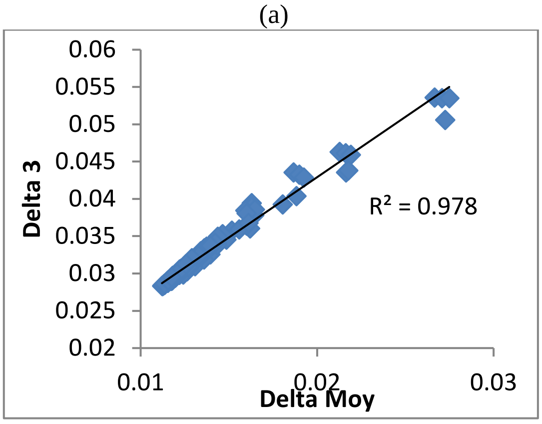
4.4 Comprehensive comparison between $\Delta^{(m)}$ estimates

The associated uncertainties $\Delta^{(m)}, m = 2,..,4$ is assessed for the 125 cases Fig. 7 in order to estimate the method-to-method variability of RR estimates according to:

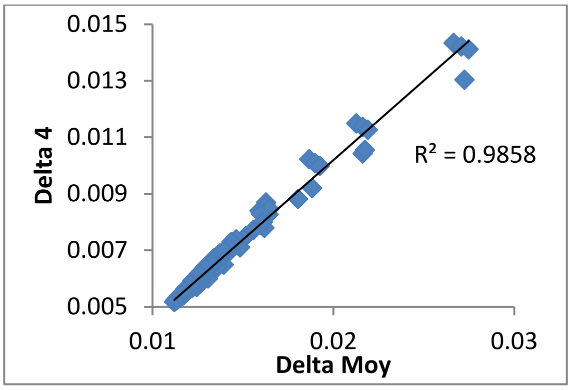
$$\Delta_M^{(m)} = \sqrt{\frac{1}{125}\sum_{j=1}^{125}\left(\Delta_j^{(m)}\right)^2} \qquad (32)$$



(a)



(b)



(c)

Fig. 7 Summary comparison for the 125 cases of Δ(m) between the different of RR for each method.
(a) : Δ (2) ; (b) : Δ(3) ; (c) : Δ(4).

4.5 Best estimate of the repair rate

Based on the previous comparative study we found that the best estimates of the repair rate is the weighted average $RR^{(4)}$ since its gives values which are the intermediate value between all other values and is confident since its standard deviation is generally the lowest.

The last section will gives a general idea on the variation of the repair rate computed using weighted average $RR^{(4)}$ and for instance one of the GMPE at the level of an urban area.

5. CASE STUDY AT THE LEVEL OF AN URBAN AREA

As an example application, we simulate the geographical distribution of the repair rate at the scale of the city of Tlemcen (western Algeria). Even though the seismicity in this area, located 600 Km west of Algiers, is historically less pronounced than in the coastal area, significant earthquakes cannot be ruled out, especially as there is a mapped fault (fault plateau of Terni) [9] located about 5 kms to the south of the city with a length of about 21 km allows to consider the possibility of events up to Mw magnitude 6.5. Such a "worst case" scenario has thus been considered as an illustrative example, and the weighted average repair rate has been estimated (method#4, as described in Eq. (9)).

The town of Tlemcen is composed of 3 main sub-districts: Mansourah, Tlemcen and Chetouane with a well-known geotechnical information [11]. This figure 8 show also the variation of the repair rate predicted with the weighted average repair rate (method#4, Eq. (9)).

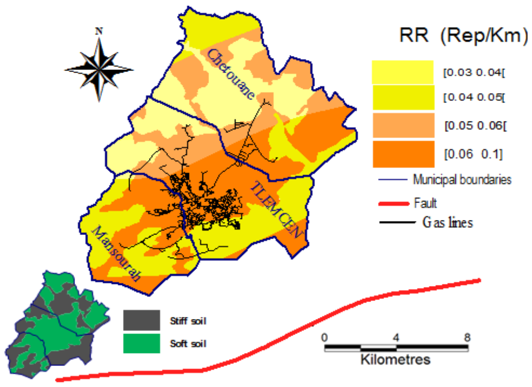


Fig. 8 Map of the mean predicted RR (using the models 4) for the city of TLEMCEN for a scenario earthquake of M =6.5 occurring on the southern fault (red line).

6. CONCLUSION

Repair Rate per kilometer (RR) is one of the most suitable tools to measure the fragility of lifeline structures after earthquake. Seismic analysis of the buried pipelines is important since the number of the required information used is very important. Indeed engineers needs to know which soil types and seismic actions are be used in the analysis.

RR use seismic parameters which in turn are derived from numerous approaches described by by attenuation relationship also known as GMPE (Ground Motion Prediction Equation). This later has great variability which was extensively studied and assessed.

In this paper a methodology that takes into account the inherent variability of the ground motion parameters has been developed. This methodology has been applied for the case where the seismic parameter is expressed in terms of Peak ground velocity (PGV). It worth noting that the developed methodology could be applied for other models that used other seismic parameters like for instance on the peak ground acceleration (PGA).

The newly developed approach leads to the establishment of weighted average repair rate instead of unique repair rate.

These weighted average values of RR are then compared to conventional values obtained for a single GMPE and without uncertainty.

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