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Empirical model for frequency content estimation of strong ground motion records of Iran

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ABSTRACT
This paper presents a new empirical model to predict the mean period (T m) as a frequency-content parameter of earthquake record using the strong ground motions recorded in Iran during 1975–2019. An updated earthquake databank containing 2281 horizontal acceleration records was employed to develop the empirical model through a systematic fitting procedure. A simple functional form for the model was found as a function of epicentral distance (R), moment magnitude (Mw), and the shear wave velocity averaged at the top 30 m of the recording sites (V s30). The proposed model is compared with three existing predictive models and the results are discussed in terms of magnitude, source-to-site, and site dependencies.

1. Introduction
The frequency content of seismic ground motions can significantly affect the seismic response of structures and geo-structures (e.g., Kramer, 1996; Rathje et al., 2004; Kumar et al., 2011; Jafarian and Lashgari, 2016). The distribution of amplitude versus different frequencies is described by the frequency content parameters (Kramer, 1996). It is well understood that civil engineering systems can potentially receive much more seismic demands when frequency-content of input motion is closer to the fundamental period of the system (Kramer, 1996; Chopra, 2001; Rathje et al., 2004).

The mean period (T m) of an earthquake record, as a scaler frequency content parameter is commonly employed for different design purposes. Previous studies indicated that T m as a meaningful intensity measure (IM) can provide a suitable prediction of the seismic response for the engineering systems such as structures (e.g., Kumar et al., 2011; Song et al., 2014; Bravo-Haro and Elghazouli, 2018; Hickey and Broderick, 2019) and geo-structures (e.g., Rathje and Antonakos, 2011; Rathje et al., 2014; Jafarian and Lashgari, 2017; Lashgari et al., 2020). Moreover, in recent decades, T m is widely used to estimate the seismic-induced displacement of slopes (e.g., Rathje and Bray, 1999; Saygili and Rathje, 2008; Jafarian and Lashgari, 2016; Tsai and Chien, 2016; Jafarian et al., 2018; Lashgari et al., 2018; Lashgari et al., 2020). In general, higher frequency waves could lead to shallow landslides and lower frequency shaking affects deeper areas in the slope (Bourdeau et al., 2004; Jibson and Tanyaş, 2020). Jibson and Tanyaş (2020) indicated that the mean period as a frequency content parameter is apparently the best predictor of the earthquake-induced landslide size distributions. In recent decades, T m is widely used to develop the predictive models of seismic sliding displacement (e.g., Rathje and Bray, 1999; Saygili and Rathje, 2008; Jafarian and Lashgari, 2016; Tsai and Chien, 2016; Jafarian et al., 2018; Lashgari et al., 2018; Lashgari et al., 2020). Accordingly, prediction of T m can play an important role to predict landslide hazard in seismic regions. T m is calculated using the Fourier amplitude spectrum (FAS) according to Rathje et al. (1998, 2004) as follows:

\[ T_m = \frac{\sum C_i (1/f_i)}{\sum C_i^2} \]  

(1)

where C i, f i, and Δf are the Fourier amplitude coefficient, the discrete fast Fourier transform (FFT) frequencies between 0.25 and 20 Hz, and the frequency interval used in the FFT computation, respectively.

The ground-motion prediction equations (GMPEs) have been recently presented to predict IMs for design purposes (e.g., Ulusay et al., 2004; Atkinson and Boore, 2007; Campbell and Bozorgnia, 2007; Lin et al., 2013; Jafarian et al., 2014); Bastami and Sohrat, 2017; Zafarani et al., 2017; Farajpour et al., 2019). A few GMPEs have been proposed to estimate T m although it is a valuable IM for prediction of the seismic response of an engineering system. Rathje et al. (2004) developed a...
preceeding model proposed by Rathje et al. (1998) using an extended ground motion database and predictor variables. Yaghmaei-Sabegh (2015) proposed an empirical model using several Iranian earthquake ground motions. A database of global earthquake ground motions was employed by Du (2017, 2019) to develop a predictive model for $T_m$. Chousianitis et al. (2018) presented a model for $T_m$ prediction using the earthquake data recorded in Greece.

Iran has been recognized as a tectonically active region in the world. A large database of earthquake ground motions has been compiled by Road, Housing, and Urban Development Research Center (BHRC) of Iran. Iran is exposed to spread phenomena of landslides, especially in the Alborz-Azerbaijan and Zagros mountains (Jafarian et al., 2019). There are numerous structures (e.g., buildings) and geostructures (e.g., slopes) located in Iran that are often exposed to seismic hazards such as earthquake-induced landslides. Development of predictive models for $T_m$ based on the ground motions recorded in Iran could lead to more desirable estimation of seismic and geotechnical hazards.

In the current study, a new predictive model is presented to estimate $T_m$ in Iran plateau based on a large database of earthquake ground motion accelerations recorded in this seismic region. The collection of Iran’s earthquake records employed in the current study is primarily presented in this paper. Subsequently, the predictive model of $T_m$ is generated by the systematic multiple regression analysis as a simple function of the epicentral distance ($R$), the shear wave velocity at top of 30 m ($V_{S30}$), and the moment magnitude ($M_w$). Finally, performance of the model is evaluated by the parametric study and comparison with a regional-scale and two global-scale models.

2. The Strong Motion Dataset

The Iran plateau is compressed by the Arabian and Eurasian tectonic plates. The tectonic activities of the Iran plateau were mainly controlled by the convergence of the Arabian and Eurasian plates that leads to moderate to large shallow crustal earthquakes by the strike-slip and reverse faults (e.g., Berberian, 2014; Zafarani and Soghrat, 2017). The recent Sarpol-e Zahab earthquake (2017, $M_w = 7.3$) triggered significant damages in the western of Iran where the Arabian and Eurasian plates collide (Zafarani et al., 2020).

The Iranian Strong Motion Network (ISMN) which is now part of BHRC was established in 1973 to record earthquake input motions by installing of recording stations. More than 10,000 three-component time series of acceleration, which includes a pair of horizontal acceleration and one vertical acceleration components, were recorded by ISMN in Iran during 1975–2013 (Zafarani and Soghrat, 2017). Moreover, more than 1700 three-component time series of acceleration were recorded by more than 833 stations during 2013–2019. In this study, an extended database of the ground motion records from ISMN (including 1975–2019 acceleration records) was employed to develop an empirical model for $T_m$. The database was composed of 4562 accelerations records of two horizontal components (H1 and H2) associated with 536 earthquakes occurred during 1975–2019. The locations of stations and events were shown in Fig. 1. The multi-resolution wavelet analysis (Ansari

![Fig. 1. Location of stations and epicenters of Iranian earthquakes records used in this study.](image-url)
et al., 2010) was used to eliminate unsuitable noise from the earthquake records. This analysis was also employed by Zafarani and Soghrat (2017) for the filtering of the Iranian earthquake records. Moreover, the baseline correction was made for all used records. The Euclidean norm of the $T_m$ ($\sqrt{T_{m,H1}^2 + T_{m,H2}^2}$) were used for each pair of horizontal components (H1 and H2) because the Fourier transform space is a vector space (Rathje et al., 2004). Finally, one $T_m$ was obtained for one station in one event. However, the averaging method in this study is different from the approach used by Rathje et al. (2004) who employed combination of Fourier spectrums of two components to calculate $T_m$. Geometric mean was also employed by other researchers such as Chousianitis et al. (2018) to estimate averaged $T_m$. The current model is presented for the prediction of the Euclidean norm of the horizontal components of $T_m$.

The different source-to-site distances such as Joyner-Boore ($R_{JB}$),
rupture ($R_{rub}$), hypocentral ($R_{hyp}$), and epicentral (R) distances are employed to develop GMPEs, each one has advantages and disadvantages. $R_{jb}$ and $R_{rub}$ are measured on the basis of the fault geometry and the rupture plane and can lead to a more accurate GMPE. The $R$ and $R_{hyp}$-based GMPEs can be used to estimate the ground-motion field when only the epicentral location has been determined immediately following an earthquake (Bommer and Akkar, 2012). The lack of detailed information about fault geometry and the rupture plane for most earthquakes in Iran prevented the use of $R_{jb}$ or $R_{rub}$ in this study. However, the authors acknowledge that $R_{jb}$ and $R_{rub}$ are crucial need for the development of an accurate model. Based on Chousianitis et al. (2018), $R_{hyp}$ was not used to avoid bias due to poorly resolved focal depths. Accordingly, $R$ was employed to develop the predictive model in this study.

Table 1
The values of “a” coefficients and the results of the regression [Eq. (2)].

<table>
<thead>
<tr>
<th>$V_{S30}$ (m/s)</th>
<th>Coefficient</th>
<th>$M_w &lt; 5$</th>
<th>$5 \leq M_w &lt; 6$</th>
<th>$6 \leq M_w &lt; 7$</th>
<th>$7 \leq M_w$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{S30} &lt; 360$</td>
<td>$a_1$</td>
<td>-1.477</td>
<td>-1.3447</td>
<td>-1.04</td>
<td>-0.9257</td>
</tr>
<tr>
<td></td>
<td>$a_2$</td>
<td>-0.979</td>
<td>-0.9745</td>
<td>-0.9677</td>
<td>-0.9706</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.035</td>
<td>0.043</td>
<td>0.044</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.032</td>
<td>0.034</td>
<td>0.038</td>
<td>0.109</td>
</tr>
<tr>
<td>$360 \leq V_{S30} &lt; 560$</td>
<td>$a_1$</td>
<td>-1.7316</td>
<td>-1.6554</td>
<td>-1.0674</td>
<td>-1.0816</td>
</tr>
<tr>
<td></td>
<td>$a_2$</td>
<td>-0.9633</td>
<td>-0.9598</td>
<td>-0.9716</td>
<td>-0.9697</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.029</td>
<td>0.011</td>
<td>0.021</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.011</td>
<td>0.006</td>
<td>0.014</td>
<td>0.014</td>
</tr>
<tr>
<td>$560 \leq V_{S30} &lt; 760$</td>
<td>$a_1$</td>
<td>-1.7756</td>
<td>-1.6802</td>
<td>-1.301</td>
<td>0.0889</td>
</tr>
<tr>
<td></td>
<td>$a_2$</td>
<td>-0.973</td>
<td>-0.9688</td>
<td>-0.9678</td>
<td>-1.0157</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.011</td>
<td>0.022</td>
<td>0.019</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.006</td>
<td>0.013</td>
<td>0.016</td>
<td>0.015</td>
</tr>
<tr>
<td>$760 \leq V_{S30}$</td>
<td>$a_1$</td>
<td>-1.8366</td>
<td>-1.9018</td>
<td>-1.4409</td>
<td>-1.6235</td>
</tr>
<tr>
<td></td>
<td>$a_2$</td>
<td>-0.9693</td>
<td>-0.9572</td>
<td>-0.9646</td>
<td>-0.9518</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.028</td>
<td>0.029</td>
<td>0.024</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.008</td>
<td>0.013</td>
<td>0.021</td>
<td>0.597</td>
</tr>
</tbody>
</table>

Fig. 5. Distribution of $T_m$ and $V_{S30}$ of 2281 used ground motions.

Fig. 6. Variations of $T_m$ versus $R^{Mw}$ and the proposed model [Eq. (2)] for different classes of shear wave velocity and moment magnitude.
due to the resonance effect within soil layers. This phenomenon can significantly affect the frequency content of input motions (Du, 2017). Accordingly, $T_m$ as a frequency content parameter is influenced by site conditions. The local site conditions are represented by $V_{s30}$ on the GMPEs. This parameter can help to investigate the resonance phenomena of a site. However, the use of $V_{s30}$ alone for the site effect assessment could be challenging, since the shear wave is tied to soil rigidity (Castellaro et al., 2008). The site classification is generally used to evaluate the local site effect on the GMPEs by the values of $V_{s30}$ according to the standards or guidelines criteria (e.g., Eurocode, NEHRP). However, new approaches have been recently proposed for site classification which can better show the site effects (e.g., Kotha et al., 2018; Del Gaudio et al.,

Fig. 7. The “a” fitting coefficients with respect to the variations of shear wave velocity for various moment magnitudes.
show that normal faulting causes higher amplitude/Tm values than the focal mechanism of the events (e.g., Rathje et al., 2004). Previous studies (e.g., Zhao et al., 2016; Chousianitis et al., 2018; Xu et al., 2019). The focal mechanisms are not considered in this study since the focal mechanisms (e.g., Chousianitis et al., 2018; Xu et al., 2019) are developed for unknown focal mechanisms. However, different GMPEs were developed for unknown focal mechanisms (e.g., Zhao et al., 2016; Chousianitis et al., 2018; Xu et al., 2019). The focal mechanism is not considered in this study since the focal mechanisms were not presented in detail in the database of Iranian strong motion records.

The frequency content of the ground motion can be affected by the local site condition in this study by soil categorization released by the standards of National Earthquake Hazards Reduction Program (NEHRP). As shown in Fig. 2(c), less than 1% of records fall in site class E (soft soil, \( V_{s30} \leq 180 \text{ m/s} \)), 19.2% in site class D (stiff soil, \( 180 \leq V_{s30} < 360 \text{ m/s} \)), 49.6% in site class C (very dense soil and soft rock, \( 360 \leq V_{s30} < 760 \text{ m/s} \)), and 31.2% in site classes B (rock, \( V_{s30} \leq 1500 \text{ m/s} \)) and A (hard rock, 1500 m/s ≤ \( V_{s30} \)). Fig. 2(d) indicates that the values of \( T_w \) vary in different ranges between 0 and 3 s. However, its average is about 0.25 s.

The distribution of \( M_w \) was plotted with respect to the epicentral distances of the earthquake records database per different site classes in Fig. 3. The strong ground motion records are separated based on the recording dates for two ranges between 1975 and 2013 and 2013–2019 in Fig. 3. It demonstrates that the average moment magnitude is about 5, 5.3, and 5.9 for the recorded earthquakes in the site classes B, C, and D, respectively. Moreover, the average epicentral distance is about 40, 59, and 107 km for the recorded earthquakes in the site classes B, C, and D, respectively. As shown in this figure, the average moment magnitude in the database is around 5.5 while the average epicentral distance is about 63 km.

The variations of \( T_w \) were plotted versus the epicentral distances for three levels of magnitude such as low, moderate, and high in Fig. 4. The strong ground motion records are distinguished on the basis of the recording dates in Fig. 4. As shown in this figure, the value of \( T_w \) decreases when \( M_w \) or R decreases. The average value of \( T_w \) is about 0.28, 0.42, and 0.91 s for \( M_w < 5 \), 5 ≤ \( M_w < 6 \), and \( M_w \geq 6 \), respectively. Fig. 4 shows that the epicentral distance of data is around 24, 47, and 127 km.

### Table 2

The values of “a” coefficients and the results of regression [Eqs. (3-4)].

<table>
<thead>
<tr>
<th>“a” coefficient</th>
<th>Coefficient</th>
<th>( M_w &lt; 5 )</th>
<th>( 5 \leq M_w &lt; 6 )</th>
<th>( 6 \leq M_w &lt; 7 )</th>
<th>( 7 \leq M_w )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_1 )</td>
<td>( b_1 )</td>
<td>-45.192</td>
<td>-87.254</td>
<td>-140.14</td>
<td>-201.47</td>
</tr>
<tr>
<td></td>
<td>( b_2 )</td>
<td>-0.4977</td>
<td>-0.4483</td>
<td>-0.5575</td>
<td>-0.4038</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.028</td>
<td>0.003</td>
<td>0.043</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.695</td>
<td>0.077</td>
<td>1.086</td>
<td>1.242</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>( b_3 )</td>
<td>1.3471</td>
<td>6.7902</td>
<td>3.0412</td>
<td>10.31</td>
</tr>
<tr>
<td></td>
<td>( b_4 )</td>
<td>-1.0328</td>
<td>-1.0498</td>
<td>-1.039</td>
<td>-1.0611</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>0.003</td>
<td>0.0001</td>
<td>0.002</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>RSE (%)</td>
<td>0.081</td>
<td>0.004</td>
<td>0.059</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Wald and Allen (2007) presented a methodology for deriving maps of \( V_{s30} \) anywhere in the world using topographic slope as a proxy. A global \( V_{s30} \) map server was provided by The U.S. Geological Survey (USGS) earthquake hazard program (https://earthquake.usgs.gov/data/vs30/) based on Wald and Allen (2007) and Allen and Wald (2009)’s models.

The values of \( V_{s30} \) are taken into account as the local site condition in this study by soil categorization released by the standards of National Earthquake Hazards Reduction Program (NEHRP). As shown in Fig. 2(c), less than 1% of records fall in site class E (soft soil, \( V_{s30} \leq 180 \text{ m/s} \)), 19.2% in site class D (stiff soil, \( 180 \leq V_{s30} < 360 \text{ m/s} \)), 49.6% in site class C (very dense soil and soft rock, \( 360 \leq V_{s30} < 760 \text{ m/s} \)), and 31.2% in site classes B (rock, \( V_{s30} \leq 1500 \text{ m/s} \)) and A (hard rock, 1500 m/s ≤ \( V_{s30} \)). Fig. 2(d) indicates that the values of \( T_w \) vary in different ranges between 0 and 3 s. However, its average is about 0.25 s.

The distribution of \( M_w \) was plotted with respect to the epicentral distances of the earthquake records database per different site classes in Fig. 3. The strong ground motion records are separated based on the recording dates for two ranges between 1975 and 2013 and 2013–2019 in Fig. 3. It demonstrates that the average moment magnitude is about 5, 5.3, and 5.9 for the recorded earthquakes in the site classes B, C, and D, respectively. Moreover, the average epicentral distance is about 40, 59, and 107 km for the recorded earthquakes in the site classes B, C, and D, respectively. As shown in this figure, the average moment magnitude in the database is around 5.5 while the average epicentral distance is about 63 km.

The variations of \( T_w \) were plotted versus the epicentral distances for three levels of magnitude such as low, moderate, and high in Fig. 4. The strong ground motion records are distinguished on the basis of the recording dates in Fig. 4. As shown in this figure, the value of \( T_w \) decreases when \( M_w \) or R decreases. The average value of \( T_w \) is about 0.28, 0.42, and 0.91 s for \( M_w < 5 \), 5 ≤ \( M_w < 6 \), and \( M_w \geq 6 \), respectively. Fig. 4 shows that the epicentral distance of data is around 24, 47, and 127 km.
for $M_w < 5$, $5 \leq M_w < 6$, and $M_w \geq 6$, respectively.

Fig. 5 shows the variations of $T_m$ versus $V_{30}$ for three levels of magnitude. As shown in this figure, there is a meaningful relationship between the variations of $T_m$, $V_{30}$, and $M_w$. Fig. 5 indicates that the value of $T_m$ decreases when $V_{30}$ increases for all levels of magnitude. Moreover, the value of $T_m$ increases with the magnitude in a constant $V_{30}$.

3. The predictive model of $T_m$

The mean period as a frequency content parameter can be affected by the magnitude, distance, focal mechanism, and site shear wave velocity. Accordingly, most presented models were developed based on these parameters (e.g., Rathje et al., 1998). The evaluation of the GMPEs shows that the models are generally functions of site effect, the magnitude and focal mechanism (e.g., Rathje et al., 2004; Yaghmaei-Sabegh, 2015; Du, 2017; Chousianitis et al., 2018). The combination of these parameters can provide an accurate model for prediction of $T_m$. However, simultaneous attention to accuracy and simplicity can increase the applicability of the model for engineering purposes. In this study, three parameters comprising the epicentral distance, the moment magnitude, and site shear wave velocity were nominated to generate the model of $T_m$.

The former studies of authors demonstrated that the data classification per small ranges of parameters can decrease the scattering of data and increase the correlation coefficient in a regression analysis (e.g., Lashgari et al., 2018; Jafarian et al., 2019). Accordingly, the correlations between $T_m$ and relative parameters were investigated for some small ranges of $M_w$ within each site class.

Different functional forms were evaluated in each data class to achieve the optimum functional form. Finally, the best model was chosen based on three criteria: (1) the physical concept of $T_m$; (2) the simplicity to increase the applicability of the model, (3) the accuracy by consideration of the model residuals. These selection criteria are commonly used to choose the most appropriate functional forms (e.g., Du, 2017). Moreover, the value of R-squared ($R^2$), the relative standard error (RSE), and the standard error (SE) were used to assess efficiency of the functional forms. The regression procedure is performed on the basis of the linear regression process which takes the best functional form as follows:

$$\ln T_m = a_1 + (1 + a_2) \ln R M_w \pm \sigma_{\ln T_m}$$ (2)

where $T_m$, $a_1$, and $a_2$, $R$, $M_w$, and $\sigma_{\ln T_m}$ are the mean period in second, the constant coefficients as a function of the moment magnitude and shear wave velocity, the epicentral distance in km, the moment magnitude, and the standard deviation of the proposed model, respectively.

The data of $T_m$ were plotted versus $\ln R M_w$ for several categories of
site classes and three levels of magnitude in Fig. 6. The moment magnitude was classified into four levels of magnitude including low ($M_w < 5$), moderate ($5 \leq M_w < 6$), high ($6 \leq M_w < 7$) and very high ($M_w \geq 7$) for regression analyses. The predictive model [Eq. (2)] was individually fitted for each category of $V_{s30}$ and $M_w$ to obtain "a" coefficients by the multiple regression procedure. As shown in Figs. 4-5, the recorded data follow a reasonable trend versus the variations of $V_{s30}$ and $R$ when $M$ is divided into different classes. Accordingly, the data were categorized into four groups of $M$ and $V_{s30}$. The "a" coefficients as a function of $V_{s30}$ and $M_w$ were calculated for all data groups. The effect of parameter variations can be appropriately evaluated in a predictive model by multiple regression procedures (Lashgari et al., 2018; Jafarian

Fig. 11. Variations of the predicted values of $T_m$ versus the variations of (a) $M_w$; (b) $R$; (c) $V_{s30}$.

Fig. 12. 3D plot of the variation of $T_m$ versus the variations of $M_w$ and $R$ for (a) $V_{s30} = 350$ m/s; (b) $V_{s30} = 650$ m/s; (c) $V_{s30} = 950$ m/s.
It was noted that the constant coefficients are supposed as a function of M, R, and V_{s30} in this study. However, Eq. (2) represents a basic form as a function of M and R and it was expected that the coefficients were supposed to only be dependent on V_{s30}. The correlation between the coefficients and V_{s30} was firstly investigated without classifications of M. Despite many efforts, a reasonable relationship was not found to describe the correlation between the variations of the coefficients versus V_{s30}.

The “a” coefficients (a1 and a2), the relative standard error (RSE), and the standard error (SE) were shown in Table 1 for each class of V_{s30} and Mw. The evaluation of the “a” coefficients indicates that they have a clear correlation with the variations of V_{s30} in a constant site class and different categories of Mw. Accordingly, the τ_{s30} values were classified into four groups of V_{s30} for each class of moment magnitude.

The distribution of the “a” coefficients was plotted with respect to the variation of V_{s30} per four magnitude classes in Fig. 7. The values of V_{s30} are an average of V_{s30} data for each magnitude class. As shown in Fig. 7, a correlation can be found to predict the “a” coefficients based on the variations of the shear wave velocity or Mw. A clear correlation can be found to predict the variation of V_{s30} against the variations of Mw. Despite many efforts, a reasonable relationship was not found to describe the correlation between the variations of the shear wave velocity or Mw as the variable factors. The values of SE and RSE of Eqs. (5–8) were shown versus four magnitude classes in Table 2. The best-fit equations form between the “b” coefficients and the moment magnitude are presented as follows:

\[ b_1 = M_w / (-0.1765 + 0.201M_w) \]  
\[ b_2 = M_w / (3.828 - 2.805M_w) \]  
\[ b_3 = M_w / (5.47 - 0.6474M_w) \]  
\[ b_4 = M_w / (-2.2327 - 0.915M_w) \]

where \( b_1 \), \( b_2 \), \( b_3 \), and \( b_4 \) are dependent on the moment magnitude as the variable factors. The values of “b” coefficients, SE, and RSE were shown in Table 2.

The framework of the predictive model of Tauw is summarized in the following equations:

\[ \text{Ln } T_{\text{m}} = a_1 + (1 + a_2) \text{Ln } R^{\text{Mw}} + \sigma_{\text{Ln } T_{\text{m}}} \text{ for } M_w \leq 7 \]

in which

\[ a_1 = [M_w / (-0.1765 + 0.201M_w)] + [M_w / (3.828 - 2.805M_w)] V_{s30} \]  
\[ a_2 = [M_w / (5.47 - 0.6474M_w)] + [M_w / (-2.2327 - 0.915M_w)] V_{s30} \]

The moment magnitude of 7 (M_w = 7) was assumed in Eq. (9) for M_w.
7. A simple C#-based tool was written for possible application of the model. This tool is presented as the supplemental data. As shown in Figs. 3-5, the available data do not uniformly cover all ranges of input parameters $M_w$, $R$, and $V_{s30}$. For example, there is not fairly amount of data within $6.5 < M_w < 7$ or $R > 200$ km. Therefore, applicability of the proposed model might be limited in these ranges and the model has to be improved in the future.

4. Model evaluation and comparison

The variation of the predicted values of the proposed model [Eq. (9)] were plotted versus the input variable variation of $M_w$, $R$, and $V_{s30}$ in Figs. 11 (a-c). Fig. 11 (a) indicates that the $T_m$ follows an increasing trend for different distance when moment magnitude increases. The difference of $T_m$ with increasing of $M_w$ so that it is around 1.25 times for $R = 10$ and $R = 100$ km in $M_w = 4$ and 1.85 in $M_w = 7$. Fig. 11(b) indicates that the $T_m$ values increase at different levels of magnitude when the epicentral distance changes. However, its increasing trend declines for $R > 50$ km. Fig. 11(c) shows that the variation of $V_{s30}$ has exponentially affected the mean period. $T_m$ decreases with increasing of $V_{s30}$ so that it decreases around 1.35 times when $V_{s30}$ enhances from 300 to 1000 m/s given a constant distance. Figs. 12 (a–c) indicate 3D plots of $T_m$ with the values of $M_w$ and $R$ for different values of $V_{s30}$ including 350, 650, and 950 m/s. These plots can
provide a suitable perspective of the $T_m$ estimation compared with Fig. 12, since they demonstrate the dependency of $T_m$ on different parameters, such as $M_w$, $R$, and $V_{s30}$, concurrently. As shown in Fig. 12, the variations of contour lines of $T_m$ values follow a gentle variation for low magnitudes. The variation of $T_m$ increases for medium ($5 \leq M_w < 6$) and high ($6 \leq M_w < 7$) magnitudes. It was assumed constant for very high magnitude ($7 < M_w$). The comparison between the values of $T_m$ indicates that it decreases from 0.77 to 0.59 for $V_{s30} = 350$ m/s and $V_{s30} = 950$ m/s, respectively, in $R = 50$ km and $M_w = 6.5$.

To the author’s knowledge, a few empirical models have been proposed to predict $T_m$ (Rathje et al., 1998; Rathje et al., 2004; Yaghmaei-Sabegh, 2015; Du, 2017; Chousianitis et al., 2018). The presented models by Rathje et al. (1998), Rathje et al. (2004), and Du (2017) were developed using the ground motion database of the worldwide earthquakes. The regional models were proposed by Yaghmaei-Sabegh (2015) and Chousianitis et al. (2018) for Iran and Greece, respectively. The properties of the models are outlined in Table 3.

As shown in Table 3, the predicted models are a function of different variables, while these parameters ($R_{rup}$, $Z_{tor}$, $I_{dir}$, $Z_1$, and FD) are not available for the available strong motion database of Iran. Hence, the effects of these variables ($Z_{tor}$, $I_{dir}$, $Z_1$, and FD) are ignored in the current comparative study. Moreover, the values of $R_{rup}$ were not reported for
the Iranian input motion database and Ris used as the distance parameter of the recorded data. Accordingly, $R_{up}$ was assumed to be equal $R$ in the models of Rathje et al. (1998), Rathje et al. (2004), Yaghmaei-Sabegh (2015), Du (2017). Moreover, the models of Rathje et al. (2004), Yaghmaei-Sabegh (2015), and Chousianitis et al. (2018) used an indicator variable ($S_i$ and $S_j$) to designate site classes. Rathje et al. (1998)'s model was proposed for soil and rock sites. The models of Du (2017) and this study were developed based on the continuous $V_{30}$ parameter as a preferable site response variable for GMPEs (Kamai et al. 2014). The authors acknowledge the fact that some of the differences can be resulted in due to assumptions (e.g., distance, depth, and directivity), particularly for the models of Rathje et al. (1998), Rathje et al. (2004), Yaghmaei-Sabegh (2015), and Du (2017). The models proposed by Rathje et al. (1998), Rathje et al. (2004), and Du (2017) were developed based on the global ground motions with different tectonic characteristics. The current model, however, is a regional one, which was developed using the ground motion database of Iran. Hence, some of the differences between the models prediction can also be attributed to the source of data and regionalization of the dataset.

The predicted values of $T_a$ by the models developed by Rathje et al. (1998), Rathje et al. (2004), Yaghmaei-Sabegh (2015), Du (2017), Chousianitis et al. (2018), and the current model (Eq. [9]) were plotted versus the variations of distance for $V_{30} = 270$, 560, and 1000 m/sand $M_w = 5.5$ and 6.5 in Fig. 13. The values of $V_{30}$ were assigned as 270, 560, and 1000 m/s for site classes D, C, and B based on the average velocity in each site class. Fig. 13 indicates that the value of $T_a$ is incrementally predicted for all site classes by all of the models when $R > 50$. Figs. 13(a, c, and e) show that the current model provides a high value of $T_a$ compared with the other models for $M_w = 6.5$. As shown in Figs. 13(b, d, and f), the current model predicts $T_a$ in the middle range of other models. However, the difference between the current study and Yaghmaei-Sabegh (2015) is small for site classes D and C when $R > 50$. Fig. 13 indicates that the presented model estimates different results compared with the Yaghmaei-Sabegh (2015)'s model as a regional model for Iran especially at $R < 50$ km for site classes D and C. However, they have a significant difference in site class B. The different strong motion database has potentially affected the fitting procedure as well as the selected functional form. As shown in Table 3, Yaghmaei-Sabegh (2015)'s model was developed using 575 records while the current model employed a larger database including 2281 earthquake records. The strong motion database used in the current model covers a wide range of site classes and magnitudes (see Fig. 2).

Fig. 14 illustrates the variations of the values of $T_a$ versus $M_w$ for different site classes predicted by the current model and the models developed by Rathje et al. (1998), Rathje et al. (2004), Yaghmaei-Sabegh (2015), Du (2017), and Chousianitis et al. (2018). Fig. 14 indicates that all the models follow an incremental trend when $M_w$ increases. The model of Rathje et al. (1998) provides larger predictions for $M_w < 6$ while the results of Chousianitis et al. (2018) is smaller for $M_w < 6.5$. The results of the current model are close the results of the models of Rathje et al. (2004) and Du (2017) for $M_w < 5.5$ in all site classes. The predictive curves of this study are generally similar to the model of Yaghmaei-Sabegh (2015) for the site classes D, and C. However, difference between the current model and Yaghmaei-Sabegh (2015) is relatively high for site class B.

5. Conclusions

An empirical relationship has been proposed to predict the mean period of horizontal earthquake acceleration records using seismic events recorded in Iran. The empirical model was developed based on 4562 strong-motion records in Iran from 1975 to 2019. The model can be used to predict seismic behavior of engineering systems in Iran, especially regarding to landslides. The presented model directly correlates $T_a$ to earthquake magnitude $M_w$ and source-to-site distance $R$. However, it was indirectly correlated to $V_{30}$ through a multiple regression analysis. The residuals of the predictive model were carefully examined for the possible undesired bias versus the input variables. It is shown that the residuals are at an acceptable level so that more than 65% of residuals fall between $\pm 0.5$ (ln unit). A comparison between the results of the current and three predictive models confirmed that the current model was fitted well on the recorded data compared with the other models.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References
