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A Probabilistic Methodology for Assessing Post-Earthquake Fire Ignition Vulnerability in Residential Buildings

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Abstract. Post-earthquake fire (PEF) ignition events constitute a secondary consequence of an earthquake and may result in the loss of life and substantial property damage, especially in urban areas where the potential for fire spread and conflagration exists. These secondary hazards can cause severe structural and non-structural damage, potentially more significant damage than the direct damage caused by the initial earthquake, and can lead to catastrophic structural failures, devastating economic losses, and casualties. To manage the impact of PEF in urban areas, it is important to identify the potential ignition sources and quantify the vulnerabilities of these ignition sources as a result of earthquake-induced structural damage. The results of such analyses can be used to offer resiliency improvement investments and mitigation strategies in urban areas located in seismically active regions. Most of the previous PEF studies are data-driven, utilizing ignitions reported following recent earthquakes. However, in areas for which historical PEF data are not available, such as the Midwestern United States, a different methodology for developing a PEF model is needed. This paper describes an analytical model for quantifying the vulnerabilities of residential buildings to PEF by estimating the failure of ignition sources upon a probable seismic event. The underlying concept in developing the method is that (1) ignition sources in residential buildings remain unchanged before and after an earthquake, and (2) the total probability of PEF occurrence can be estimated by adjusting the probabilistic fire occurrence data for normal conditions (everyday operation of ignition sources) to account for the effect of the earthquake. This paper's contribution to state of the art is in developing a new framework for estimating the probability of PEF for areas in which historical PEF data is unavailable. The developed framework uses the likelihood of ignition occurrence during normal condition as a baseline; this baseline is then adjusted using certain key parameters to capture spatial characteristics, ignitability, and potential seismic intensity of the study area to estimate the probability of PEF as a function of projected earthquake characteristics. The model was tested for St. Louis City as a populated area with potential future earthquake hazard because of its proximity to the New Madrid Fault zone. Using the National Fire Incident Reporting System dataset, the frequency of normal condition

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ignitions was determined as 1.97E−03 ignition per unit per year. Using the proposed PEF model considering PEFs caused by damage to drift and acceleration sensitive equipment and human actions, the projected frequency of PEF was estimated between 2.79E−06 and 2.81E−06 ignitions per household per year. Using this model, and the average number of households between 2010 to 2015, 175,854 households, it was estimated that in the next 50 years, approximately 25 households would experience fires related to probable earthquake events in St. Louis City.

Keywords: Post-earthquake fire, Vulnerability assessment, Probabilistic modeling, Ignition sources

1. Background

1.1. Overview of Ignition Sources

Fires following an earthquake can increase the adverse consequences of an earthquake, cause substantial damage and lead to a widespread disaster [1–7]. The adverse consequences of post-earthquake fires (PEFs) and the challenges in identifying the location of ignitions following an earthquake, estimating the number of ignitions, and evaluating the fire spread mechanism have motivated researchers to focus on these topics over the past 20 years. PEFs have been observed following several large earthquakes, including the Northridge (1994) [2] and Loma Prieta (1989) earthquakes [5] in US; the two earthquakes in Christchurch New Zealand (2010 and 2011) [8]; and the Hanshin (Kobe) (1995) [9] and Fukushima (2011) earthquakes in Japan [10]. Post-earthquake fire studies can be grouped into three different categories including, (i) fire initiation, which focuses on the local level of PEFs [11–14], (ii) fire spreads [9, 15, 16], and (iii) fire suppressions [17]. The last two categories can be categorized as the global level of PEF [18]. Improving fire initiation models to estimate the probability of ignitions following an earthquake enhance the realism in estimating fire spread, and as such will provide better input for risk mitigation strategies. The significance of PEF in populated areas is that such events may spread to large areas, hampering the emergency response and impeding the rescue activities at the time that these services are vitally needed [6]. To manage the impact of PEF on urban areas, quantification of the prevalent risk and preparation of a mitigation strategy for future hazard are necessary. Methods to estimate the risk of PEF are especially beneficial to engineers and architects in urban planning design and in the estimation of the potential economic losses.

Fire in urban areas can be started from an ignition within buildings. Structural damages may cause ignitions by either extensive differential displacement causing failures of system utilities (e.g., gas pipeline) or damage to the non-structural elements following building failures. Additionally, non-structural components and contents within a building (e.g., stove) can damage and result in ignitions. Zolfaghari et al. [12] categorized intra-structure post-earthquake fire ignition sources into three main groups: (i) utility networks such as gas and electricity, (ii) ignitable braced non-structural equipment such as fireplaces, (iii) ignitable unbraced equipment such as TVs. The failures of the first two categories identified by Zolfaghari depend on the structural damage, i.e., the function of earthquake lateral loads while ignitable unbraced equipment are more sensitive to earthquake

acceleration [12]. Damage occurred to household equipment, and the existence of heat sources, such as spark of electrical utilities, can result in fire initiation during an earthquake [19]. Another PEF study identified ignitions occurring in buildings due to (1) occupant behavior and (2) code deficiency of equipment and structural systems [13]. During an earthquake, occupants' increased stress and anxiety, especially in areas where earthquake events are rare, can be sources of fire following an earthquake in a building [20, 21].

It is useful to consider ignition sources in fires occurring during normal conditions (i.e., without the occurrence of externalities increasing the probability of fires). The term "normal condition," as used here, refers to the everyday operation of ignition sources. Based on the ignition data between 2003 to 2016 published by US Fire Administration (USFA),[1] which are utilized by the USFA in developing the "Fire Estimated Summary Series", two common sources of fire ignitions during normal condition are cooking and heating equipment, representing around 46.3% and 13.4% of the normal condition ignitions (excluding ignitions due to natural hazards such as high winds and floods) within residential buildings, respectively, over this time period. A 2013 Japanese firefighting white paper examining ignition sources in normal condition ignitions resulting in fatalities identified cigarettes and stoves as the two most common ignition sources, accounting for 15.6% and 11.7%, respectively, while 45.2% of the ignitions had an unknown ignition source [22].

During an earthquake, ignition sources identified in normal condition ignitions are expected to become more likely to cause an ignition. This is mainly because the ground shaking and potential structural damage during an earthquake make household equipment more vulnerable to malfunction and failure thereby increasing their probability to cause fire. On this basis, the probability of fire occurrence during everyday activities and routine operation (normal condition ignition) can be used as a baseline to evaluating PEF probability. The probability of normal condition ignition (NCI) needs to be adjusted based on the severity of probable earthquake events and the seismicity of the area [23]. Certain types of equipment (such as water heaters) are more vulnerable to ground motion and may suffer damage due to either overturning or movement and dislocation [24].

While most of the ignition sources within a building during an earthquake exist prior to an earthquake, earthquakes can create additional ignition sources that do not exist during normal conditions, such as pipeline ruptures or arcing from broken wires. These earthquake-caused ignition sources act as an additional fuel source, heat source, or both. In the current study, fuel and heat sources are not modeled independently, but rather the model evaluates fire ignitions occurrence when both fuel and heat source are present. An Analysis of the National Fire Incident Reporting System (NFIRS)[2] dataset of structural fires occurring in residential buildings following earthquakes shows that the majority of these ignitions involve equipment, particularly water heaters and stoves. This is likely due to the fact that both of these appliances have pilot lights (open flames) that will cause an

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[1] https://www.usfa.fema.gov/downloads/xls/statistics/residential_nonresidential_fire_loss_estimates.xlsx.
[2] NFIRS Pubic Data Release files (1980–2013).

ignition if exposed to fuel. For example, leaks from natural gas pipelines in a building can cause a build-up of natural gas resulting in an ignition, if the build-up reaches a heat source. Therefore, the occurrence of fires involving damage of utilities within buildings are indirectly evaluated as part of the equipment-based ignitions.

This study focuses on evaluating the impact of the spatial characteristics and the failure mechanisms of ignition sources during an earthquake. Two areas within the US are selected so that the impact of spatial characteristics, such as the geographic concentration of particular building types, can be examined. Recent California earthquakes, occurring between 1980 and 1994, were selected to ensure that the building characteristics such as building structural types are representative of the currently existing building stock. As additional PEF data becomes available from new earthquakes, the analysis can be updated to incorporate this data. Likewise, historical PEFs occurring in other countries, such as Japan and New Zealand, were not considered in this analysis as the building types, building codes, and typical operations are different in these countries than those in the US. Future research is suggested to evaluate the probability of PEFs using the proposed model for such areas. In this study, the probability of NCI for the two study areas within the US is assessed using the NFIRS dataset and the detailed PEF database of ignitions occurring for six recent US earthquakes (including ignition date, time, and location) published by Davidson et al. [14] was utilized.

1.2. Background of PEF Models

As stated in Lee et al. [25] PEF ignition models aim to assess the numbers, locations, and times of ignition following an earthquake. Several models have been developed to predict the risk of fire following an earthquake [14, 24, 26, 27]. Most such models are data driven and depend on previous statistical records [14]. Data driven models are generally utilized in PEF risk modeling due to the variety of potential ignition mechanisms and the inherent variability of ignition occurrences [14]. These models highly depend upon the spatial characteristics, such as geographic, demographic, and structural types, of the area for which the PEF data have been compiled. Lee et al. [25] provided a comprehensive literature review of ignition models. Scawthorn divided the PEF analysis into empirical and analytical approaches and introduced a hybrid approach, which is the combination of both empirical and analytical methodologies [26]. For areas with sufficient PEF data, empirical models (regression models) can be used to determine PEF frequencies by identifying the key parameters influencing PEF (e.g., earthquake intensity) [26]. Analytical models such as event tree and fault tree evaluate the event sequences leading to ignition [28]. Mohammadi et al. and later Williamson et al. [5, 28] utilized the event tree and fault tree approach to evaluate the number of PEF. Zolfaghari developed an analytical approach for modeling PEF considering the factors leading to ignitions following an earthquake using fault tree analysis [12]. Scawthorn proposed a hybrid approach using historical PEF in order to improve PEF frequency estimates. In the Scawthorn study, analysis was conducted at the census tract level and the PEF frequency (ignitions per floor area) was estimated as a

function of earthquake characteristics, i.e., Modified Mercalli Intensity [26]. Expert elicitation can also provide information on PEF key parameters [29]. In areas for which historical PEF data are not available, a different methodology to estimate PEF needs to be considered. Recently, studies have focused on explicit consideration of parameters affecting ignition occurrence. These parameters can be grouped into (i) spatial characteristics, such as building types and their response to an earthquake, (ii) ignitability characteristics such as fuel type, and (iii) earthquake characteristics such as peak ground acceleration (PGA). Davidson identified several parameters affecting PEF rate such as building category, population, structural type, and earthquake intensity [14]. Elhami Khorasani et al. [11] developed a probabilistic PEF model using historical data using Geographical Information System (GIS)-based tools. The same author previously developed an ignition model to identify the vulnerability of the community to PEF [30]. Lu et al. [31] developed a physics-based PEF simulation model, considering building failure following an earthquake. These analytical methods that are based on physical modeling of ignition sources and their influencing parameters may then offer an alternative to data-based methods [23]. These alternative methods may also be developed using the statistics of fire events under normal condition as a basis and adjusting these statistics to account for the significance of an earthquake event in increasing the probability of fire initiation. The frequency of normal condition ignition can be obtained from fire incident statistics available through fire departments and other emergency response agencies.

In this paper, the proposed model for evaluating the probability of PEF for residential buildings is explained. The model is applicable to areas with insufficient historic PEF data. The primary motivation for developing the model is the need for a PEF risk estimation method for areas of moderate to high seismicity with little or no historic PEF records. With urban development over the last several decades, some of these areas are now considered as high density population regions, and thus more vulnerable to seismic damage effects, including fire. Since NCI data are generally available for these areas, the models explained in this paper may offer an alternate approach to estimate the probability of PEF. In addition to the NCI data, several key factors such as those related to (1) the geographical and spatial features of the area and the building types, (2) ignitability potentials of the sources in a building, and (3) seismicity of the area, are also included in the model. The model was tested using a seismic region for which PEF data and earthquake source parameters were available. To demonstrate its applicability, the model was used for St. Louis City which is a populated area with the potential to experience large earthquakes because of its proximity to the New Madrid Fault zone. The remainder of the paper is organized as follows. Section 2 details the data compilation process in ArcGIS. Section 3 describes the process of identifying the underlying contributing factors utilized in the proposed model. In Sect. 4, the proposed model is explained in detail, and the calibration process is presented in Sect. 4.1. In order to illustrate the applicability of the proposed model, Sect. 4.2 illustrates the application of this model for St. Louis City. Using the model, it was estimated that in the next 50 years, 25 households will experience fires related to expected earthquake events in St. Louis City.

2. Data Compilation

The development of a PEF model to estimate the probability of ignition occurrence for a given area requires adequate data on the (1) fire events caused by home appliances under normal conditions; and (2) information on the seismicity of the area including the probability of future earthquake events. Furthermore, before any such model can effectively be used, it needs to be tested for an area for which historical NCI and PEF data are available. There are several areas in the State of California for which both PEF and NCI data are available due to the occurrence of recent earthquakes. Specifically, the review of the literature reveals that the ignitions occurred in six recent earthquakes in California have been well documented and can be used as a basis to test the PEF model. The earthquakes are the Coalinga (1983), Morgan Hill (1984), Palm Spring (1986), Whittier (1987), Loma Prieta (1989), and Northridge (1994) Earthquakes. The historical PEF data for these earthquakes provides the number of ignition occurrences and the locations of all PEF ignitions [14]. More recently, there have been additional occurrences of fires following earthquakes. The most notable are six ignitions which occurred in the Napa earthquake (2014) [11]. This data became available after the proposed model had been developed and calibrated and, as such, the data has not been included in the dataset of this study. Ongoing research by the authors is currently expanding the study as a means of updating the model considering the significance of this new set of data. The probability of PEF needs to be obtained for a given residential unit and a specific peak ground acceleration (PGA) range. Thus, to estimate the probability of PEF, the number of ignitions is divided by the number of residential units experiencing a specific PGA range of each earthquake. Using the software ArcGIS [32], the number of residential units that share the same PGA range is determined. Recently, Elhami Khorasani et al. [11] utilized HAZUS and ArcGIS to compile ignition incidents, geographic and demographic information, i.e., census tract, and recorded earthquake PGA values.

In the current study, the PGA map published by the United States Geological Survey (USGS) [33] overlaid on the census tract map published by the National Historical Geographic Information System (NHGIS) [34]. In addition, the ignitions occurred in each of the aforementioned six earthquakes are added to the ArcGIS map. Figure 1 shows the PGA map for the Northridge earthquake overlaid on census tracts. Red dots are ignitions that occurred following the Northridge earthquake.

In order to estimate the probability of NCI, a similar process as explained for evaluating the probability of PEF was utilized. However, depending on the extent of the available data, the probability of NCI may be computed as a single value for the entire state or as multiple values, each representing a specific PGA range. The number of NCIs are obtained from the NFIRS data [35], and the number of residential units at each census tract are gathered from the NHGIS data [34].

It is noted that uncertainties exist in historical PEF records as not all jurisdictions may report ignitions following earthquakes, ignitions extinguished by occupants may be unreported, and multiple ignitions may occur within a building and be reported as a single ignition [13]. As such, previous studies tend to exclude
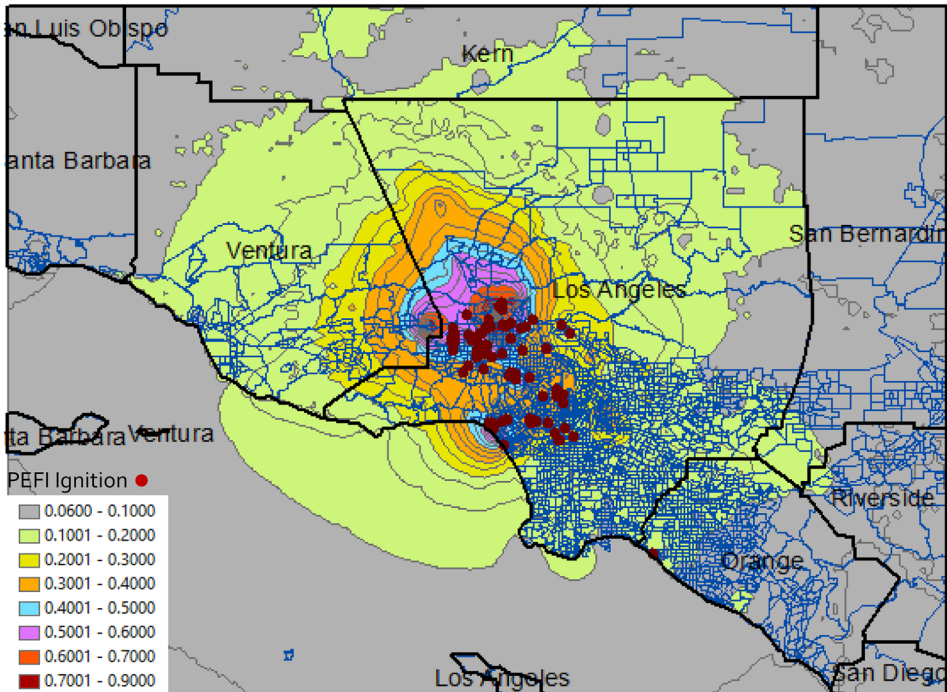
Figure 1. Location of PEF ignitions shown in red dots and peak ground acceleration values observed during the Northridge earthquake [14, 33].

those areas experiencing non-zero PGA values without reported ignitions, referred to as 'zero ignition' areas [26]. It is indicated that including zero ignitions may underestimate the probability of PEF, while excluding zero ignitions may overestimate this value [14]. In this paper, the analysis is conducted for two situations of including and excluding zero ignitions. Thus, combined with the two methods indicated for handling the probability of NCI assessment, there are four different sets of data for estimating probability of PEF and NCI. These four sets are labeled as Sets A, B, C and D as explained below.

Set A   Includes zero ignitions and uses NCI data within various PGA ranges
Set B   Includes zero ignitions and uses NCI data for the entire state as a constant value
Set C   Excludes zero ignitions and uses NCI data within various PGA ranges
Set D   Excludes zero ignitions and uses NCI data for the entire state as a constant value

3. Driving Factors in Post-Earthquake Fire Model

The driving factors in the PEF model are identified by reviewing related studies, which focus on estimating the probability of NCI and PEF. Specifically, the relative frequency of particular factors employed in previous NCI and PEF models was considered as an indicator of the importance of the factors in estimating the

probability of ignition occurrence in normal condition and following an earth-quake. The authors reviewed several previous NCI and PEF models to identify the most common parameters used in each model type. NCI models is generally utilized to estimate the ignition frequency, i.e., the number of ignitions normalized by buildings stock characteristics over a period of time [36]. Most of NCI models have utilized building floor areas and building sizes as two common factors affect-ing ignition frequency [37–39]. Building stock characteristics also affect ignition frequency during an earthquake. Several researchers have identified floor area of specific building type as a parameter in estimating ignition frequency during an earthquake. In addition, other factors such as earthquake characteristics (e.g., Modified Mercalli Intensity, PGA) identified as significant factors affecting the likelihood of PEF [29, 40, 41]. The earthquake hazard level in an area can be qualitatively described as low, moderate or high seismicity. Various measures (for example, earthquake intensity, or magnitude) can be used to describe these levels. Using the severity of an earthquake in terms of its magnitude, at 4.9 Richters or lower, the seismic activity is low, while the moderate is at 5 to 5.9 Richter range. A severe activity constitutes earthquakes with magnitudes in excess of 6 or higher Richters [42]. Lee et al. conducted a comprehensive literature review on previous post-earthquake fire models and identified covariates utilized in the PEF models. Farshadmanesh et al. [18] provided the details of significant NCI and PEF model parameters. As stated in this study, these factors are categorized in four groups, including (1) spatial characteristics (e.g., building floor areas and building cate-gories); (2) ignitability characteristics, such as availability of ignition source, fuel type; (3) seismicity of the area including the expected earthquake intensities, such as Modified Mercalli Intensity (MMI), PGA, or peak ground velocity (PGV); and (4) the time of earthquake occurrences and seasonality [18].
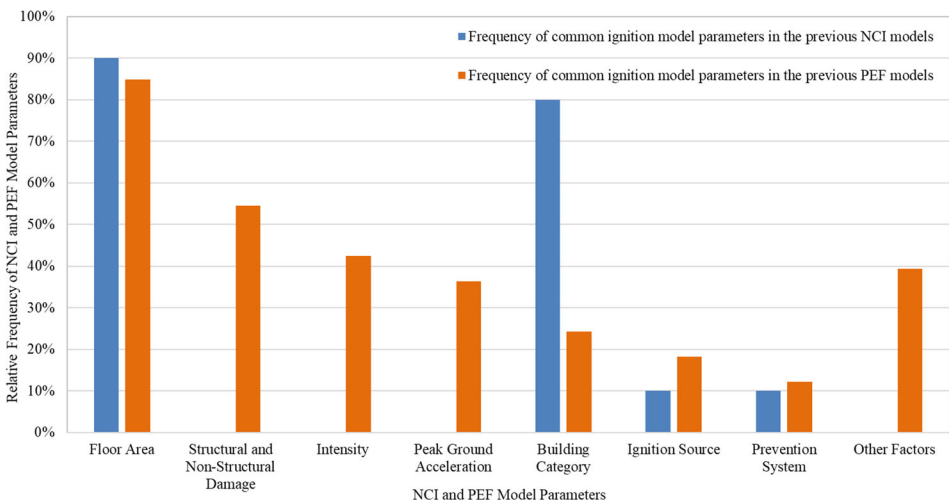
Figure 2.   Relative frequency of significant factors utilized in previous NCI and PEF studies.

The relative frequency of NCI and PEF model parameters identified from previous studies are summarized in Fig. 2. As seen in Fig. 2, floor area is a common model parameter in previous NCI and PEF models. In addition, there are few other factors were identified in previous studies such as peak ground velocity (PGV) [2, 10] which were lumped together and shown as "Other Factors" in Fig. 2. For example, Trifunac et al. [2] evaluated the density of red tagged buildings in terms of horizontal peak ground velocity in San Fernando Valley and Los Angeles after Northridge earthquake.

4. Proposed Model to Estimate the Probability of Post-Earthquake Fire

The proposed PEF model provides values for the probability that there will be at least one earthquake-related fire event in any residential building located in a given area during a given time period. The residential buildings considered in this study include single family, multi-family dwellings, and mobile homes. A source of ignition is considered to be a household appliance or equipment that may fail or malfunction and cause fire. Examples of such sources include cooking appliances and water heaters. Under normal conditions, ignitions can occur due to (1) occupant interference and behavior and (2) faulty equipment and appliances, overheated and short circuit cases and installation practices that violate the code requirements [13]. Ignitions that occur due to the occupants' interference and behavior are generally because of the misuse or mishandling of heat and igniting materials or careless exercises in using fueling techniques. Upon occurrence of an earthquake, these ignition sources still exist, except that their contributions to initiate fire will increase because of physical effects from ground shaking and potential movements of, and damage to, the structure. It is also noted that during a rare event such as an earthquake, the level of occupants' anxiety and stress is expected to rise contributing further to the potential for fire. Although the increased probability of PEF due to occupants' behavior is addressed by other researchers [20, 21], there are no specific studies that provide guidance on how to quantify the increase in PEF probability because of this factor. Nevertheless, in this paper, a coefficient to account for the significance of occupants' behavior in affecting the PEF probability is considered. This coefficient will need to be quantified in further studies which are beyond the scope of this paper.

Assuming the two major sources of ignition (i.e., human interference and behavior and equipment malfunction and deficiencies) are independent, the probability of PEF can be obtained using a negative binomial distribution (Eq. 1).

$$P_{PEF} = 1 - [(1 - P_{PEF_{Behav.}})(1 - P_{PEF_{Mal.}})] \tag{1}$$

where $P_{PEF_{Behav.}}$ is the probability of fire following an earthquake due to human interference and occupants' behavior and $P_{PEF_{Mal.}}$ is the probability of fire following an earthquake due to equipment malfunction and deficiencies.

Similar to estimating the probability of PEF, normal condition ignition sources are also considered independent, and as such, the probability of NCI within a building is determined using a negative binomial distribution (Eq. 2).

$$P_{NCI} = 1 - [(1 - P_{NCI_{Behav.}})(1 - P_{NCI_{Mal.}})] \tag{2}$$

where $P_{NCI_{Behav.}}$ is the probability of normal condition ignition due to human interference and occupants' behavior and $P_{NCI_{Mal.}}$ is the probability of normal condition ignition due to equipment malfunction and deficiencies.

In addition, it is assumed that, the probability of fire occurrence due to human behavior following an earthquake increases by α times. As indicated by Ohta and Omote, human behavior is highly correlated to seismic intensities; i.e. the increase of earthquake intensity increases human anxiety, leading to decreased human performance [43]. A recent study investigated human responses during three recent earthquakes occurred in California including the Whittier Narrows, the Loma Prieta, and the Northridge earthquakes [44]. This study focuses on the relation between human responses during these three earthquakes and the cultural and demographic factors. In the absence of any specific information, the relation between human behavior during the normal condition and an earthquake occurrence is assumed to be proportional (Eq. 3).

$$P_{PEF_{Behav.}} = \alpha * P_{NCI_{Behav.}} \tag{3}$$

By incorporating Eqs. 2 and 3 into Eq. 1, the probability of PEF can be rewritten in terms of the probability of equipment malfunction and factor α (Eq. 4).

$$P_{PEF} = 1 - \left[\left(1 - \alpha \left[1 - \frac{[1 - P_{NCI}]}{[1 - P_{NCI_{Mal.}}]} \right] \right) (1 - P_{PEF_{Mal.}}) \right] \tag{4}$$

in which P_{NCI} is the total probability of normal condition ignition and P_{PEF} is the total probability of fire following an earthquake.

It can be assumed that factor α is greater than one. However, it is noted that currently, there is no comprehensive study to suggest a numerical value for this parameter. Equation 4 is further expanded by designating X_1 as total probability of NCI and by introducing a coefficient β, which represents the ratio of the probability of NCI (due to equipment failure) to the total probability of NCI (Eq. 5).

$$P_{PEF} = P_{PEF_{Mal.}} \left[1 - \alpha \left(1 - \frac{[1 - X_1]}{[1 - \beta X_1]} \right) \right] + \alpha \left(1 - \frac{[1 - X_1]}{[1 - \beta X_1]} \right) \tag{5}$$

A function $F(x)$, can be defined as the ratio of the total probability of PEF to the probability of NCI (Eq. 6).

$$F(x) = \frac{P_{PEF}}{X_1} \tag{6}$$

Substituting Eq. 5 into Eq. 6, $F(x)$ can be expressed in Eq. 7.

$$F(x) = P_{PEF_{Mal.}} a_0 + a_1 \tag{7}$$

where

$$a_0 = \frac{1}{X_1} - \alpha \frac{(1 - \beta)}{(1 - \beta X_1)}$$

$$a_1 = \alpha \left(\frac{1 - \beta}{1 - \beta X_1} \right)$$

In order to estimate the probability of PEF due to equipment failure, $P_{PEF_{Mal.}}$, the seismic failure mechanism of ignition sources in a building were considered. Non-structural components are grouped in HAZUS based on their seismic behavior into two categories: (1) acceleration sensitive components (E_1) and (2) drift sensitive components (E_2) [45]. In this paper, an ignition source, such as a water heater, stove, and portable heating system, which has the potential for overturning are categorized into the E_1 group while E_2 are those ignition sources in which their failure depends on the building movement such as the inter-story drift. As these two equipment failure categories are independent, the overall probably of fire due to equipment malfunction is computed using a negative binomial distribution following the same form as shown in Eq. 1. Furthermore, the probability of PEF due to equipment malfunction can be computed as the product of the conditional probability of PEF due to equipment malfunction given PGA and the probability of PGA. The following sections provide details on computing the conditional probability of PEF due to equipment malfunction given PGA for acceleration sensitive and drift sensitive ignition sources.

4.1. Acceleration Sensitive Ignition Sources

To estimate the conditional probability of ignition occurrence of E_1 given PGA within a residential building, the conditional probability of overturning for each ignition source given PGA and the probability of getting to ignition level for the overturned ignition source need to be identified. Individual ignition sources in a building are assumed to be statistically independent. As such, the negative bino-mial distribution can be used to estimate the total conditional probability of PEF for k types of ignition sources E_1 given PGA. To determine the conditional proba-bility of PEF for each ignition source E_1 given an earthquake occurrence, three parameters related to each ignition source were identified. The parameters are (1) the probability of the existence of specific ignition source E_1 in a building, (2) the likelihood of overturning ignition source E_1 given an earthquake occurrence, and (3) the probability of overturned ignition source E_1 causing fire. Equation 8 illus-trates the conditional probability of PEF for k types of ignition sources E_1 within a residential building.

$$P_{PEF_{Mal.E_1}|PGA} = 1 - \prod_k (1 - P(E_{1k}|Bldg) \times P_{Over}(E_{1k}|PGA) \times \gamma_{1k}) \tag{8}$$

where $P(E_{1k}|Bldg)$ is the probability that the kth ignition source type E_1 exists within the residential building, $P_{Over}(E_{1k}|PGA)$ is the conditional probability of overturning kth ignition source type E_1 given PGA, and γ_{1k} is the probability of getting to ignition level for kth overturned ignition source type E_1.

To reduce the complexity of the model, the dominant ignition sources E_1 observed to cause ignitions in the previous earthquakes, were identified using the NFIRS dataset. Structural fires occurring within residential buildings which were reported in the NFIRS dataset during the six historical earthquakes were identified. The NFIRS dataset consists of 75% of reported fires within the US and not all ignitions occurring in the previous earthquakes are included in this dataset. It is noted that the equipment involved in each ignition is also reported within the NFIRS dataset. Using expert opinion, the equipment was categorized into E_1 and E_2. Additionally, equipment which does not generally exist within residential buildings, such as vending machines, was excluded. The results of this categorization show that the most common source of ignition in the six earthquakes is the water heater. The next most common equipment causing ignitions is the stationary surface unit. Thus, it is precievable to assume that at least one of these types of equipment is available in a building and can become a source of ignition. This means $(E_{1k}|Bldg) = 1$. Using fragility curves developed in previous studies, the probability of water heaters and stoves overturning, given an earthquake occurrence, can be estimated [24, 46]. It is emphasized that such probabilities will also depend on whether or not a piece of equipment is secured or strapped to a wall. Since the seismic code requirement are not the same for the entire United States, the consideration of ignition source E_1 being strapped to the wall depends on the location of the residential building in a study area. Although strapping water heater to the wall are required by the code within California [47], based on the recent survey by the Golden Gate Chapter of the American Society of Home Inspectors, 52% of strapped water heater are insufficient [48]. To provide a conservative estimation of the probability of ignition due to overturned water heaters, the fragility curve for unstrapped water heaters is considered in this study.

4.2. Drift Sensitive Ignition Sources

The conditional probability of PEF values based on sources E_2 are associated with the inter-story drift of the structure during an earthquake. HAZUS categorized damage of drift sensitive non-structural components during an earthquake into four levels of damage: slight, moderate, extensive, and complete [45]. Using the HAZUS definition for each level of damage, ignition source E_2 which are extensively or completely damaged are more likely to cause fire following an earthquake and, thus, are considered in this study. To determine the conditional probability of PEF for ignition sources E_2 given an earthquake, five parameters need to be considered and quantified. These parameters are (1) the probability of the existence of an extensively and completely damaged equipment type E_2 in a building, (2) the likelihood of equipment type E_2 getting to a specific damage level within a specific structural type and specific design level given an earthquake, (3) the probability that the structure was designed to a specific design level, (4) the

probability that a specific structural type exists in a residential building type, and (5) the probability that a damaged equipment E_2 will cause an ignition. The conditional probability of PEF due to failure of ignition sources E_2 given an earthquake event are calculated using Eq. 9.

$$
\begin{aligned}
P_{PEF_{Mal \cdot E_2}}|EQ = \sum_{R_b} \sum_{H_{B_a}} & \left(1 - \prod_j \left(1 - P(Ds_d = d_j)_{H_{B_a} R_b} \times \gamma_{2j} \right) \right) \times P(E_2|Bldg) \\
& \times P_{St}(R_b) \times P_{St}(H_{B_a}|B_a)
\end{aligned}
$$

(9)

where $P(E_2|Bldg)$ is the probability that a piece of equipment type E_2 exists within a residential building, $P(Ds_d = d_j)_{H_{B_a} R_b}$ is the conditional probability that a piece of equipment E_2 existing in a specific residential building and a particular structural type designed to a particular seismic design level reaches the jth level of damage (extensive or complete damage) given an earthquake, $P_{St}(R_b)$ is the probability that a given residential building was built to sustain one of the four seismic design levels, $P_{St}(H_{B_a}|B_a)$ is the probability that a given residential building in a region is a specific structural type, and γ_{2j} is the probability that a piece of equipment type E_2 at the jth level of damage will cause an ignition.

In the proposed model, it is assumed that the probability of the existence of an ignition source E_2, $P(E_2|Bldg)$, is equal to one. The level of damage for ignition source E_2 depends on the level of structural damage of the structure in which ignition sources are located. This, in turn, depends on the type of structure. The conditional probability of reaching a level of damage in a particular structural type given an earthquake can be obtained from information provided for 36 structural types in HAZUS [45]. Furthermore, the information regarding the seismicity of the area as well as the year that a given building is constructed is necessary. The identification of the building construction year is critical in order to take into account the seismic code provision at the time of the construction. The variables (median and standard deviation) defining fragility curves for each structural type within each seismic level are provided in HAZUS. In addition, HAZUS provides the information regarding the percentage of each structural type in different height levels within three types of residential buildings, single family, multi family, and mobile home. The three height levels utilized in HAZUS are low-rise (1–3 stories), mid-rise (4–7 stories), and high rise (8 stories or greater). While the percentages of structural types by occupancy type (single family, multi-family and mobile) and construction year given in HAZUS can be used to approximate the distribution of structural types in the current building stock, updated structural type distributions should be used when possible. Obtaining updated structural distributions may be challenging for multi-family buildings given the variety of structural types. Expert opinion or sampling through surveys could be used to estimate current structural distributions in an area of interest. To estimate the probability of single family, multi family, and mobile home within the three height levels in California, the 1997 Residential Energy Consumption Survey (RECS) micro data were utilized
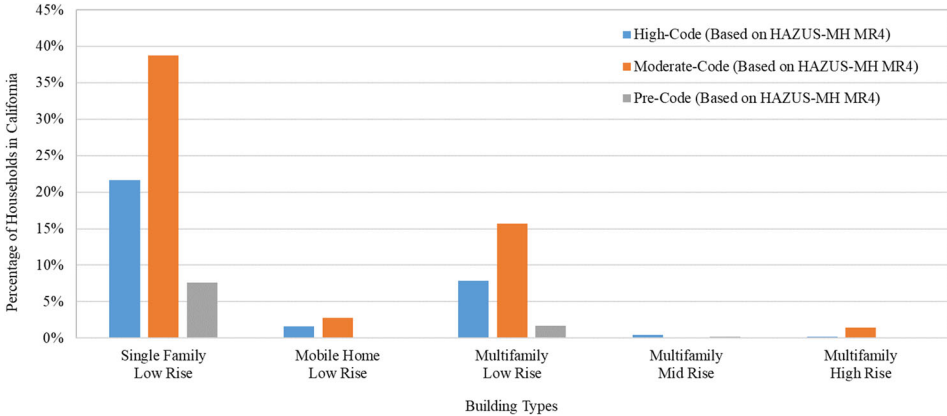
Figure 3. Distribution of residential buildings by household type, height level, and seismic design level in California [45, 49].

[49]. Figure 3 illustrates the percentage of single family, multi family, and mobile home in different height levels within high-code, moderate code, and pre-code in California. Utilizing HAZUS guidelines, buildings constructed before 1941 are grouped into a pre-code level; those constructed between 1941 and 1975 are categorized within the moderate-code level; and buildings constructed after 1975 are grouped in the high-code level [45].

The median and the standard deviation of the spectral displacement (SD) at an extensive and complete damage levels are utilized to create fragility curves. To estimate SD for a particular structural type, the PGA and spectral acceleration (SA) values, which are available for six given earthquakes—identified in Sect. 2-through USGS website [33], were converted to SD using the natural period of vibration for each structural type. The period for each structural type with a typical height [45] is estimated using ASCE 7-10 equation [50]. Finally, the conditional probability of ignition occurrence for extensively and completely damaged ignition sources E_2 are incorporated in the proposed model.

5. Model Calibration

In order to improve the predictive power of the developed model, the model is independently calibrated using each of the four previously identified datasets (A, B, C, and D). As stated in the ASME guide on verification and validation in computational models [51], model calibration is "*the process of adjusting physical modeling parameters in the computational model to improve agreement with experimental data*" [51]. Model parameters that significantly affect the model output and for which empirical data is unavailable are selected as calibration parameters. In this study, the calibration parameters within the model are the probability of ignition due to the level of damage caused by overturning of an ignition source or excessive inter-story drift (γ_{1k}, γ_{2j}) and the increased PEF probability because

of occupants' behavior (α). In addition, the probability of fire for other ignition sources in the E_1 category are lumped together and considered as a calibration parameter (Δ_{E1}). Using the generalized reduced gradient (GRG) algorithm optimization method [52], the calibrated parameter values of the proposed model are determined for each dataset. The calibrated model parameter values are those which produce the greatest coefficient of determination value. In this approach, several constraints are applied, including: (i) equipment E_1 can lead to an ignition if it overturns during an earthquake (i.e., the potential of damaged equipment causing an ignition, γ_{1k}, is greater than zero); (ii) equipment E_2 can lead to an ignition if it extensively or completely damaged (i.e., the potential of damaged equipment causing an ignition, γ_{2j}, is greater than zero); (iii) the probability of an ignition occuring is greater for a completely damaged ignition source than for an extensively damaged ignition source; (iv) as suggested by previous studies on the effect of increased occupants' anxiety and stress, the probability of occupant behavior causing an ignition will increase during an earthquake, i.e., the coefficient α, which is the probability of PEF because of occupant behavior divided by the probability of NCI due to the same source, is greater than one.

In order to calibrate the proposed PEF estimation model, the model outputs were compared with the historical data for the six previously-described California earthquakes. The results from the calibration process illustrate that the calibrated model using Datasets A and C provided greater coefficient of determination values compared with the Datasets B and D. The maximum R^2 value for the calibrated model using Dataset A and C are 0.38 and 0.63, respectively. The higher uncertainty in Dataset B and D is attributed to considering a constant value for probability of NCI for the entire state of California leads to higher variation between the results of the calibrated model and historical data. It is noted that by identifying the underlying causes of changes in occupant behavior during an earthquake, it may be possible to more accurately estimate the impact of occupants' actions on the probability of PEF. Future research is necessary to improve the estimation of the influence of an earthquake on occupant behavior. The comparison between function $F(x)$ using the model and historical data for Dataset A and C is shown in Fig. 4.

As seen in Fig. 4, the calibrated proposed model using Datasets A and C provides an approximate bound for historical data. Comparison between $F(x)$ from the calibrated PEF probability estimation model and from historical data illustrates a greater agreement in lower PGA values and higher variation in $F(x)$ for greater PGA values. Nevertheless, Fig. 4 indicates a general agreement between results from the model and historical data within limitations of the models and the variability in the aforementioned datasets.

6. Application

The application of the proposed model is considered for St. Louis City. This is a major populated area in the Midwest in the proximity of the New Madrid Fault Zone. Although there is no recent significant post-earthquake fire occurred in this area, considering the USGS Hazard map [53], there is potential for future seismic effect that
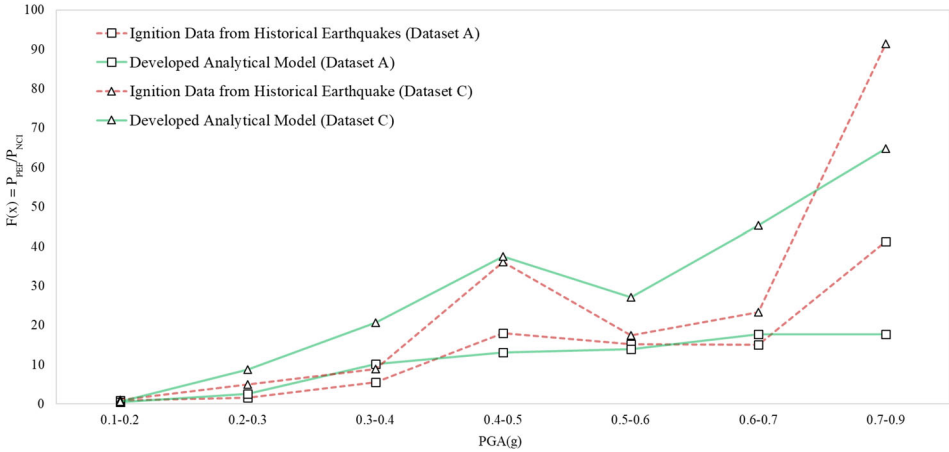
Figure 4. Comparing the results of the calibrated proposed model and the historical data using Datasets A and C.

may trigger fires. In order to estimate the probability of PEF for residential buildings in St. Louis City, the model introduced in the previous sections is employed. To illustrate the probability of PEF, the probability of an earthquake occurrence is also needed. Equation 10 shows the probability of PEF in a one year period of time.
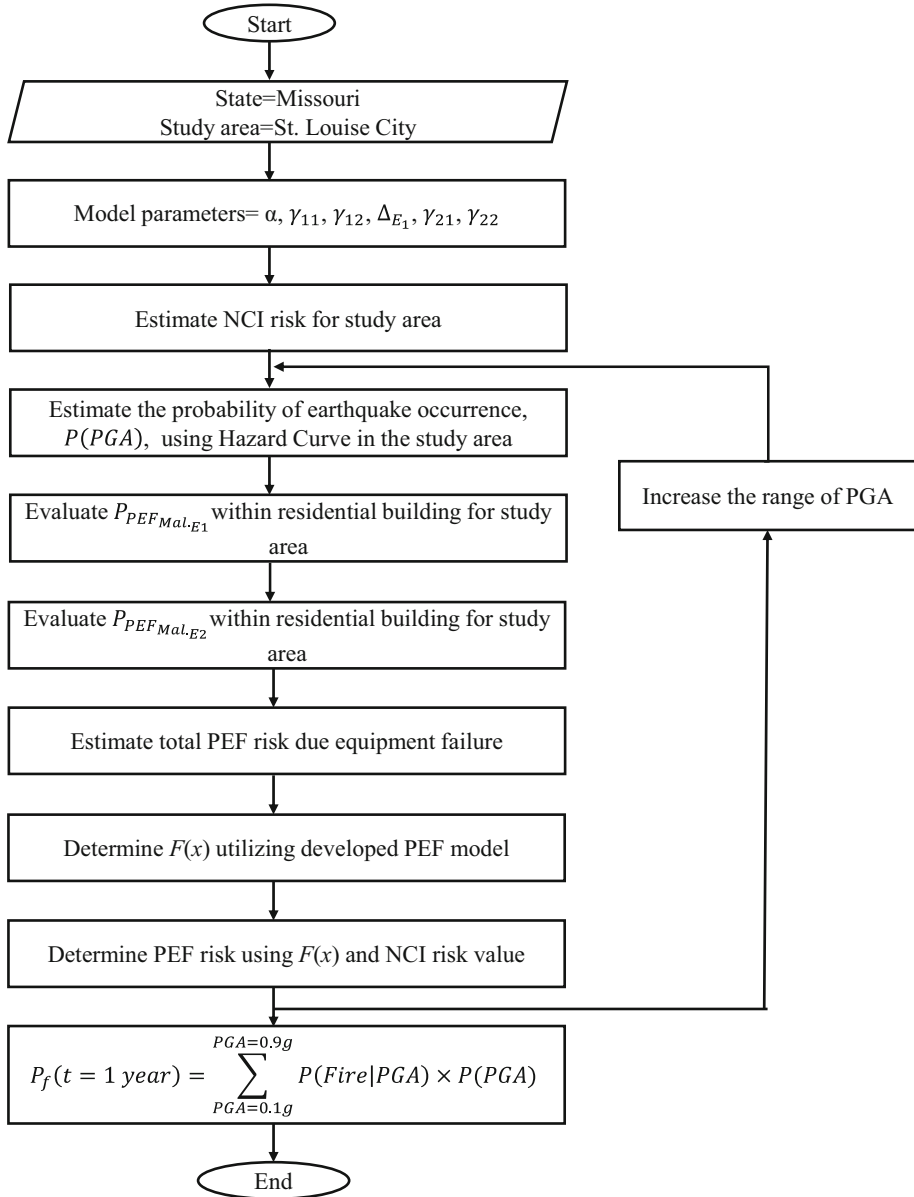
$$P_f(t = 1 \ year) = \int_{PGA} P(Fire|PGA) \times P(PGA) \tag{10}$$

where $P(Fire|PGA)$ is the conditional probability of fire following an earthquake given a specific PGA during an earthquake and $P(PGA)$ is the probability of earthquake occurrence within the specific PGA in a time frame of a year for the study area.

The process of estimating the probability of PEF for St. Louis City includes four stages, namely (1) estimating the probability of NCI using available NFIRS data, (2) estimating the probability of earthquake occurrences in St. Louis City, (3) evaluating the increased probability of PEF for various ignition sources within residential buildings in St. Louis City, and (4) applying the proposed model (Eq. 4) to estimate the probability of PEF given various PGA ranges. The flowchart shown in Fig. 5 illustrates the sequential steps involved in this process.

6.1. Evaluation of the Probability of NCI for St. Louis City

To estimate the probability of NCI, the number of NCI occurred in St. Louis City within the past few years, were obtained from the NFIRS data. Each reported ignition within the NFIRS data source has a specific Fire Department Identification (FDID) number. The FDID for each ignition source is identified to estimate the number of ignitions occurred in different localities within St. Louis City [54]. Since the goal of this study is to assess the probability of PEF within a residential building, the nonresidential building fires were not considered. Using

Start

State=Missouri
Study area=St. Louise City

Model parameters= $\alpha, \gamma_{11}, \gamma_{12}, \Delta_{E_1}, \gamma_{21}, \gamma_{22}$

Estimate NCI risk for study area

Estimate the probability of earthquake occurrence, $P(PGA)$, using Hazard Curve in the study area

Evaluate $P_{PEF_{Mal.E_1}}$ within residential building for study area

Evaluate $P_{PEF_{Mal.E_2}}$ within residential building for study area

Estimate total PEF risk due equipment failure

Determine $F(x)$ utilizing developed PEF model

Determine PEF risk using $F(x)$ and NCI risk value

Increase the range of PGA

$$P_f(t = 1 \; year) = \sum_{PGA=0.1g}^{PGA=0.9g} P(Fire|PGA) \times P(PGA)$$

End

Figure 5. Framework of proposed model in estimating the probability of PEF for St. Louis City.

the United States Census Bureau data sets (years 2011–2015), the number of residential units for St. Louis City was determined [55]. Finally, the probability of NCI were estimated by dividing the number of ignitions over the number of residential units. This resulted in estimating the frequency of NCI equal to 1.97E−03

ignitions per unit per year. In order to estimate coefficients a_0 and a_1 in Eq. 7, the parameter β needs to be quantified. Using NFIRS data for St. Louis City, the value for β is determined to be 57%.

6.2. Estimation of the Probability of Earthquake Occurrence

The likelihood of earthquake occurrence within a particular PGA value was calculated using the annual hazard exceedance curves suggested by USGS [56], which provide the annual frequency of exceedance in terms of various PGA values.

6.3. Determination of the Probability of Equipment Failure

Since Datasets A and C provided a greater coefficient of determination value in the analysis, the model's parameters for these two datasets were utilized. As described in Sect. 4, equipment involved in ignition can be grouped into equipment which are sensitive to acceleration (E_1) and to drift (E_2). To be able to predict the increased probability of ignition occurrence caused by equipment E_1 subjected to an earthquake, it is assumed the dominant ignition sources for St. Louis City are similar to that in California. Therefore, a water heater and stove will be two common ignition sources E_1 used in the analysis.

To estimate the probability of PEF of ignition source E_1, probability that E_1 ignition sources exist in a residential building needs to be determined. Additionally, the probability that a piece of equipment will overturn when an earthquake with a specific PGA occurs is evaluated. The model parameters for Datasets A and C were utilized to evaluate the probability of PEF for damaged equipment.

The probability of PEF for the ignition source E_2 was determined using fragility curves (as described earlier). It is assumed that at least one complete or extensive damaged ignition source exists within the building during the earthquake. The mean value and standard deviation for creating fragility curve for 36 structural type in HAZUS were determined at different height levels, i.e., low-rise, mid-rise and high-rise for Missouri. Using the seismic zone map in Uniform Building Code (UBC) [57], St. Louis City is located on Zone 2A. As such, buildings constructed before 1940 are assumed to follow the pre-code level, while buildings constructed after 1940 are grouped in low-code level in HAZUS [45]. The percentage of single family, multi-family, and mobile homes at pre-code and low-code level and within three height levels (low-rise, mid-rise, and high-rise) are then calculated. Based on data from RECS in 2009, multi-family buildings will be categorized into (1) 2–4 unit multi-family, (2) 5 or more unit multi-family [58]. Since there is no data available to identify height levels for multi-family with 2–4 units within RECS 2009, the 1997 RECS dataset [49], which covers additional details for building heights, was utilized. The 1997 RECS data source indicates that multi-family buildings with 2–4 units in Missouri are grouped into low rise buildings. Figure 6 shows the percentage of residential buildings within two seismic levels and three height levels for Missouri.

Finally, the PEF model parameters for ignition source E_2 were utilized to evaluate the probability of fire occurrence for ignition sources E_2. Using the model parameters for Datasets A and C results in two fragility curves for estimating probability of PEF, as shown in Fig. 7. The red dashed line represents the proba-

bility of PEF using the model calibrated using Dataset A, in which zero ignitions were included in the dataset. The green line indicates the probability of PEF due to equipment failure using the model calibrated using Dataset C when zero ignitions are removed from the dataset. The bound between these two curves illustrates the probability of PEF due to equipment failure in St. Louis.

6.4. *Evaluation of the Probability of PEF for St. Louis City*

By substituting the conditional probability of PEF due to equipment failure (rather than the probability of PEF as shown in Eq. 5) and probability of NCI
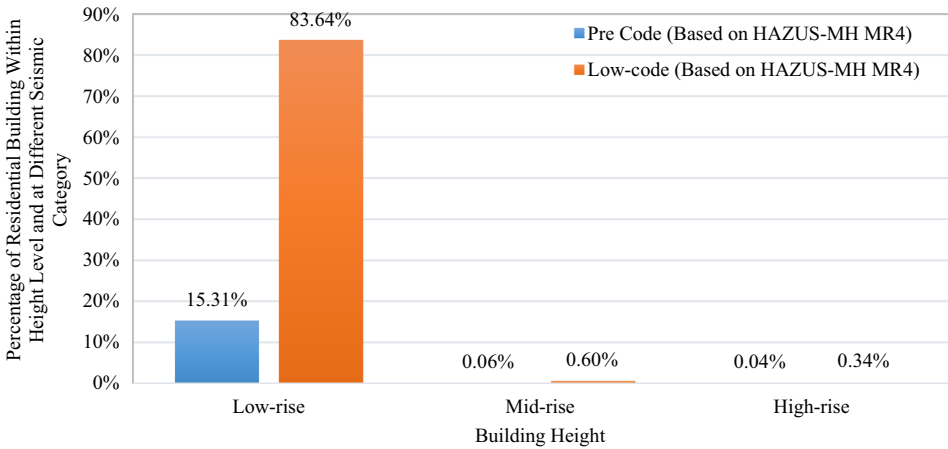
Figure 6. Percentage of residential buildings in terms of their heights for pre-code and low-code seismic levels for Missouri.
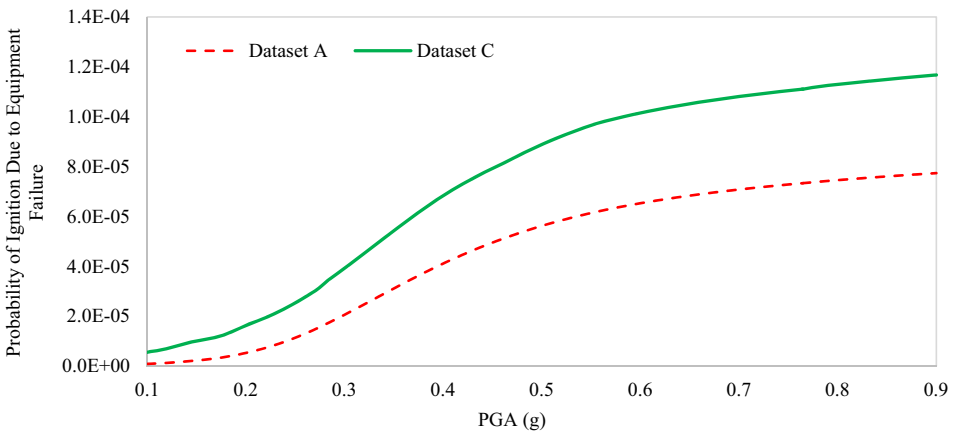
Figure 7. Developing fragility curves using Datasets A and C to assess PEF vulnerabilities of residential buildings in St. Louis City.

into Eq. 5, the conditional PEF probability is calculated. Substituting this value along with the probability of earthquake occurrence in a year into Eq. 10, the total frequency of PEF within St. Louis City is determined to be between 2.79E−06 and 2.81E−06 ignitions per household per year. Utilizing the average number of households in St. Louis between 2010 through 2015 (175,854 households), it is found that 25 households are expected to experience fire following earthquakes over a 50 years period.

6.5. *Significance of Data Uncertainty in Fire Estimates*

The model presented herein uses a probabilistic approach in estimating the probability of fire following an earthquake. The probability of fire is then translated into an estimate for potential number of fires expected in a given time period. Several sources of uncertainties enter the process including those from (1) data sets utilized for model calibration; (2) modeling of equipment failure; and (3) estimation of the residential building stock in the area. While the probabilistic formulation in estimating the fire probability incorporates the significance of uncertainties in the results, the estimates for the number of potential fires, to a great extent, will depend on the uncertainty in the values obtained for the stock of residential buildings. HAZUS data, Census data, and RECS data are used in obtaining these values. However, they are subject to variations because of a variety of reasons including uncertainty in classification of units, non-reported cases, missing data on new construction, etc. Estimates of indicators such as populations and energy consumptions are also suggested and used as measures for determining the stock of buildings [59]. Census data on population and other indicators provided by the American Community Survey are subject to margins of error that can be sizeable [60]. The 2015 data on housing by the American Housing Survey of the United States Census Bureau for sixteen major metropolitan areas indicates the margin of error in the data ranging between 1.8 and 5.4% with an average of 3.3%. Using the upper bound value of 5.4%, will result in the estimated number of fires over a 50-year period at 25 ± 1.4.

7. Broader Applications

To increase the resiliency of, and develop mitigation strategies for, urban communities, the estimation of multi hazard conditions is critical. In order to alleviate the impact of PEF within residential buildings, it is necessary to estimate the probability of PEF. In this regard, the proposed model offers several broader applications as described below.

(1) To urban planners and developers, the prediction of the likelihood of fire initiation and identification of common ignition sources are useful information when appropriate response strategies (in terms of facilities and manpower) are considered in urban planning and development projects.

(2) To local code authorities, the model presented in this study can be used in investigating the impact of fire prevention equipment, such as emergency shut-

off valves, and equipment damage mitigation technologies, such as using water heater straps, in mitigating the risk. As such, local codes and regulations may advise on implementing and enforcing certain measures to enhance building safety.

(3) To insurance companies, the results from the model can be incorporated in an overall regional risk analysis in identifying populated areas prone to higher levels of property losses and damage.

8. Conclusions

To mitigate the impact of post-earthquake fire in residential buildings, the identification of dominant ignition sources and estimation of increased probability of each ignition source given an earthquake occurrence is necessary. Since most PEF risk estimation models have been developed using data from previous earthquake records, a new methodology is proposed for an area with no or little historical record of PEFs. In this paper, the development of a framework for PEF probability assessment using the normal condition ignition probability as a basis is discussed. The findings of this study indicate that the vulnerability of residential buildings to post-earthquake fires can be approximated using the likelihood of normal condition ignitions as a baseline and then modifying this baseline based on parameters such as the potential seismicity of the study area, the geographical concentration of residential buildings, and the common ignition sources within a building during an earthquake. These factors were determined by reviewing previous NCI and PEF models and identifying the frequency of NCI and PEF model parameter usage. In addition to the effect of equipment failures during an earthquake on the probability of PEF occurrence, the impacts of potential human errors and consideration of the occupant behavior on fire initiation are highlighted. That is, ignition sources in a residential building are categorized into two groups: those related to the occupant interference and behavior and those related to the equipment failure and malfunction. The results of the analysis show greater agreement between the calibrated proposed PEF probability estimation model and historical data at lower PGA values.

   Based on the proposed model, the probability of failure for two types of equipment based on their responses during an earthquake will be determined. The probability of normal condition ignition is estimated and considered as an input in the developed model. By using the proposed model, the increased probability of ignition following an earthquake over the probability of NCI will be determined. To highlight the applicability of the proposed model to estimate the probability of PEF for an area with limited or no record of recent PEFs, the likelihood of PEF for St. Louis City was determined as a case study. Further research is necessary to improve the model by more directly modeling the impact of occupant behavior on ignition occurrence during an earthquake.Publisher's NoteSpringer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Acknowledgements

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