A Holistic Seismic Risk Scheme Using Fuzzy Sets
Part One: The Social System Fragility

J. Rubén González [1], Àngela Nebot[2], Francisco Mugica[2], Martha-Liliana Carreño[3] and Alex H. Barbat[3]

[1] *IUSS UME School Via Ferrata 45, Pavia, Italy*

[2] *Soft Computing Group, Technical University of Catalonia, Jordi Girona Salgado 1-3, Barcelona, Spain*

[3] *International Center for Numerical Methods in Engineering, Technical University of Catalonia, Jordi Girona Salgado 1-3, Barcelona, Spain*

Keywords: Fuzzy Sets, Risk Management, Natural Hazards, Vulnerability Index, Social Vulnerability, Seismic Vulnerability, Inference System.

Abstract: Hazard related Risk is a strange concept since its represents something that has not happened yet, something which is blur and randomness related. Along its estimation, social vulnerability aspects come to arise. Such aspects are even more difficult to define in part because there is still missing a robust way to quantify them and, therefore, to establish a clear analytic framework useful to understand inherent complexities of a human society. In this paper, we build a social aggravation coefficient fuzzy model considering Cardona-Carreño aggravation descriptors. By reducing the number of aggravation descriptors and establishing fuzzy logic rules between them, we found similar results in tendency and spatial distribution for seismic resilience and fragility at Barcelona, Spain. We used a classical Mamdani fuzzy approach, supported by well established fuzzy theory, which is characterized by a high expressive power and an intuitive human-like manner. We believe that in this way, a more clear analyses of the resilience and fragility bond can be done exploiting in a more suitable way fuzzy logic capabilities, because the inference process to obtain an aggravation coefficient is based precisely on the establishment of rules (*if-then type*) directly over the involved variables in social vulnerability formation which allows a smooth application of risk management knowledge, encouraging debate over the used rules, besides the discussion among the employed membership functions.

1 INTRODUCTION

Social vulnerability is one of the key factors to assembly risk in space and time, however, such important element is largely ignored over ex-ante, ex-post and cost/lost estimation reports, in part because the measurement of social vulnerability is not quite understood, and in part because the presence of epistemology oriented-based discrepancies along vulnerability definition, which binds a particular methodology with the orientation where such definition has been used, i.e. ecology, human, physical, etc. Therefore, there is a concept discrepancy when a social vulnerability model is about to be built. Diverse models have been used to obtain social vulnerability estimations. For example Cutter et al. (2003) used a hazard of-place model to examine the components of social vulnerability to natural hazards among US counties through the development of a vulnerability index based on the reduction of variables by a factor analysis plus an additive model. Kumpulainen (2006) using ESPON Hazards integrative model, created a vulnerability index map for all Europe regions based on an aggregated model, considering that regional vulnerability is measured as a combination of damage potential (anything concrete that can be damage) and the coping capacity. The principal difference between these models rely on one basic definition: while in Cutter's model the hazard potential is dependent on risk and mitigation, in ESPON model risk is a combination of the same hazard potential and the regional vulnerability.

Carreño et al. (2012) proposed an seismic aggravation risk model based on Cardona's conceptual framework of a risk model analysis for a city considering a holistic perspective, thus describing seismic risk by means of indices (Cardona, 2001) and assessing risk with the expression known as Mocho's equa-

González R., Nebot À., Mugica F., Carreño M. and Barbat A..
A Holistic Seismic Risk Scheme Using Fuzzy Sets - Part One: The Social System Fragility.
DOI: 10.5220/0005129808280835
In *Proceedings of the 4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (MSCCEC-2014), pages 828-835
ISBN: 978-989-758-038-3

tion in the field of in the field of disaster risk indicators. They propose that seismic risk is the result of physical risk (those elements susceptible to be damage or destroyed) and an aggravation coefficient that includes both, the resilience and the fragility of a society. Although the model was intended to be applied to assess the risk over a city when it is strike by an earthquake, the structure of the social vulnerability module of the model, (the one who deals with resilience and fragility), can easily be transformed in a non-disaster dependent analytic framework.

In this article, we propose a complete Mamdani fuzzy aggravation model starting from the aggravation descriptors described in Carreño et al. (2012). The aggravation model synthesizes the social aggravation characteristics of a city struck by an earthquake that could conduct to social vulnerability enhancement or moderation. A main advantage of the proposed model is its white box nature that results in a high level understandability model. Moreover, the fuzzy approximation used in this paper is well stablished and with solid background.

2 PREVIOUS MODELS

Many times the strength of a vulnerability model becomes weakened not because the type or resolution of the models themselves but because the lack of information and accurate data, in such a way that the results achieved are misleading in many ways [1]. Furthermore, the lack on understanding about how accurately measure vulnerability is one of the major uncertainty sources among social models. In most of the cases, social vulnerability is described using the individual characteristics of people (age, race, health, income, type of dwelling unit, employment, gross domestic product (GDP), income, etc.) Just in recent time, vulnerability models started to include place inequalities, such as level of urbanization, growth rates and economic vitality (Carreño et al., 2012).

Although there is a general consensus about some of the major factors that influence social vulnerability, disagreement arise in the selection of specific variables to represent these boarder concepts (Cutter et al., 2003).

The proposed model by Cardona (2003) focus on considering risk, as the possible economic, social and environmental outcomes when a seismic might occur over a period of time. Following a holistic approach,

[1]Sometimes redirecting towards a definition staying that vulnerability is a characteristic and not a condition, leading towards the assumption that without damage, or a specific hazard, vulnerability places could stand forever

Table 1: Descriptors used for aggravation estimation (Carreño et al., 2012).

AGGRAVATION DESCRIPTORS
Marginal Slums
Population Density
Mortality Rate
Delinquency Rate
Social Disparity
Hospital Beds
Human Health Resources
Emergency and Rescue Personnel
Development Level
Emergency Operability

the model puts in practice a multidisciplinary view, which considers not only the expected physical damage among infrastructures and structures, numbers of victims and economic losses, but also those conditions related with social fragility and lack of resilience that can enhance the generation of second order effects, due the earthquake. Therefore, the variables needs to address towards specific indexes or indicators related with physical vulnerability, the susceptibility of exposed elements to be damage considering potential seismic intensities over a period of time, and the context vulnerability which is dependent of social fragility and lack of resilience of urban systems with the potential to be harm because a disaster. The descriptors used by (Carreño et al., 2012) for aggravation estimation can be seen in the table 1.

2.1 Index Method

Carreño et al. (2012) obtained a seismic risk evaluation for Barcelona city by means of indicators that leads to the calculation of a total risk index. This is obtained by direct application of Moncho's equation described in 1:

$$R_T = P_R(1+F) \tag{1}$$

where R_T is the total risk, P_R is the physical risk and F is a aggravation coefficient.

Thus Carreño's model considers that seismic risk is produced for both: physical and an aggravation coefficient; this coefficient provides an approximate vision of the state of the social capital infrastructure.

The F coefficient depends on a weighted sum of an aggravation factors set associated to socioeconomic fragility of the community (F_{SFi}) and lack of resilience of exposed context (F_{LRj}), according to equation 2.

$$F = \sum_{i=1}^{m} w_{SFi}F_{SFi} + \sum_{i=1}^{n} w_{LRj}F_{LRj} \tag{2}$$

where w_{SFi} and w_{LRj} are the assessed weights on each factors calculated by an analytic hierarchy process (Carreño et al., 2007; Saaty and Vargas, 1991), and m and n the total number of descriptors, of fragility and lack of resilience, respectively. The descriptors of the socioeconomic fragility and lack of resilience of exposed context where obtained from existent databases and statistical data for the studied area.

One of the issues arising from Moncho's equation is the consideration that F can be up to much twice the value of P_R, which is not always accomplished, because some times the indirect effects are much larger than the direct effects, leading a mislead in risk estimation.

2.2 Carreño's Fuzzy Method

Taking the objective of build a more flexible risk management tool when information is incomplete or is not available, Carreño et al. proposed the use of fuzzy logic tools and expert opinion to replace indexes by fuzzy sets. The same descriptors are used and the sequences of calculations are similar to those made in the caonventional index method, however the aggravation's descriptors values which were originally obtained by demographic data bases are replaced by local expert opinions. Using linguistic qualifiers, instead of using numerical values, the aggravation value can be evaluated. Distinct linguistic descriptors qualifiers where proposed, which range in 5 levels of aggravation description: *very low, low, medium, high, very high*. Using local expert opinion, a membership function was defined for each linguistic level used to link the reported demographic or expert opinion value to one level of aggravation.

With the positive link between a reported data and its suitable linguistic level, the level is then grouped into another set of membership functions, (based on expert opinion or strictly arbitrary) which plays as a homogenizer since it blends the original qualifier level into a new single fuzzy set.

They calculated the fuzzy union between social fragility and lack of resilience descriptors, $\mu_f(x_{SF},x_{LR})$, and applied on each of these new membership functions, μ, the weights, w, corresponding to the level of aggravation, L_F, of each descriptor x_{SFi} and x_{LRj}, as defined in equation 3.

$$\mu_f(x_{SF},x_{LR}) = max(w_{SF1}\mu_{FL1}(L_{F1})...w_{LR11}\mu_{FLI}(L_{F1})) \tag{3}$$

The proposed weighted and union methods between social fragility and lack of resilience descriptors can be seen in Figure 1.

In the same way of index's method, weights are

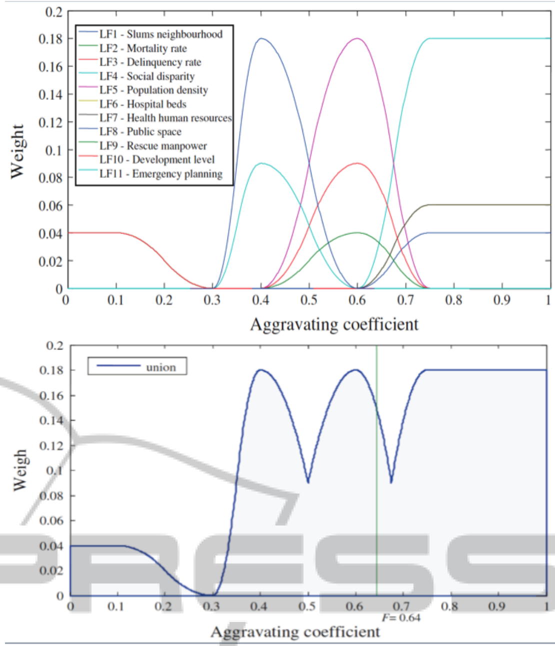

Figure 1: Carreño weighting (up) and union method (low) for San Martí District, Barcelona Spain (taken from Carreño et al., 2012).

assigned to each fuzzy set by using an analytic hierarchy process. The aggravation coefficient F is calculated as the centroid abscise of the area beneath the curve obtained with Equation 3.

We think that the Carreño's fuzzy model presented in this section is not entirely appropriate because it is a non-conventional fuzzy approach, which may be questionable due to the fact that fuzzy mathematical raised in the inference process is not well established and accurately validated.

3 CLASSICAL FUZZY METHOD

The model proposed in this research pretend to build the same aggravation coefficient by re-defining their variables into three different Fuzzy Inference Systems (FIS), called: resilience, fragility and aggravation. Each subsystem is defined by a set of rules directly over the aggravation descriptors. A conceptualization of the different steps along the proposed model can be seen in Figure 2. The variables involved in each subsystem are presented in the left hand side of Figure 2. FIS #1, corresponds to the Fragility model and has as input variables the Marginal Slums (MS), the Social Disparity Index (SDI) and the Population Density (PD). The output of FIS #1 is the level of Fragility. On the other hand, FIS #2 corresponds to the Resilience model and has as input variables the

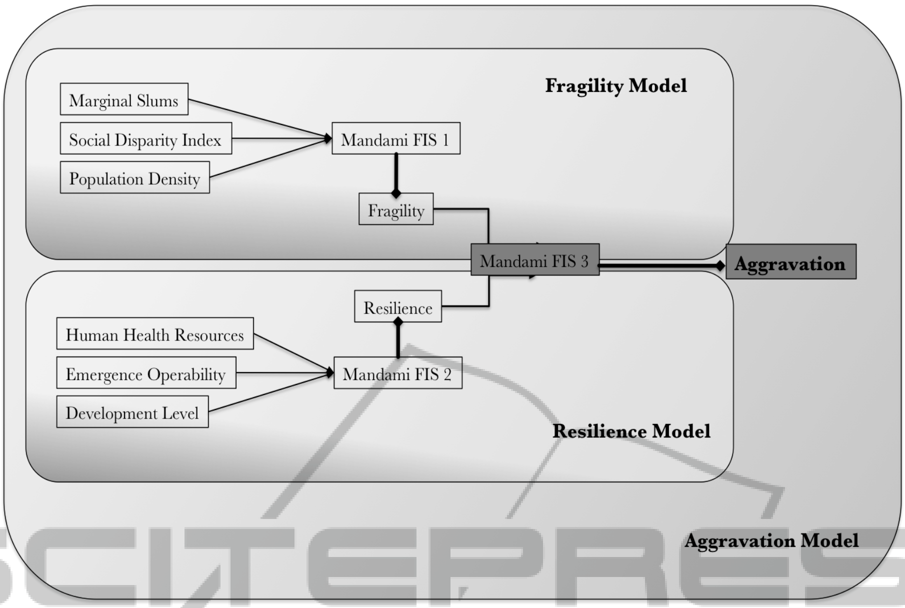

Figure 2: Conceptualization of Fuzzy Classical Model to estimate Aggravation Coefficient.

Human Health Resources (HHR), the Emergency Operability (EO) and the Development Level (DL). The output of FIS #2 is the Resilience level. The Aggravation model (FIS #3) takes as inputs the fragility and resilience levels that are the output of FIS #1 and #2, respectively, and infers the aggravation coefficient. All the fuzzy inference systems proposed in this research are based on the Mamdani approach (Mamdani and Assilian, 1975), since it is the one that better represents the uncertainty associated to the inputs (antecedents) and the outputs (consequents) and allows to describe the expertise in an intuitive and human-like manner. Our main objective is to develop a fuzzy aggravation model as much interpretable as possible and with high expressive power. In our approach the original ten variables presented in Table 1 are reduced to six variables. Population density, Slum area or marginal slums, Human health resources and Development level remain the same, and Social disparity index and Emergence operability are redefined in such a way that subsume the other variables. The reduction or simplification of the original variables was made by taking advantage of certain descriptors that are linked and could englobe various descriptors in one single class considering its social nature, for example: the descriptors called: mortality rate and delinquency rate, are related between them and are reflecting social consequences produced by a social structure failure (could be lack of access) to certain social advantages, such as having an efficient public health program, or no marginalization dynamics, or access to education and effective justice and law policies. Therefore we consider these descriptors could be enclosed within the descriptor called social disparity index, which is a fragility descriptor as well. In the case of resilience descriptor we merge descriptors called: Public Space, Hospital beds, and Emergency Personnel, into the descriptor called Emergence Operability, because the former descriptors acts when the emergency is being or has recently occurred, and therefore are related with the capacity of the city to face an emergence situation, and the assets that a city has to confront it. We modify fuzzy classes by reducing the number of linguistic levels defined for each descriptor up to 3 (*low, medium, high*) along their respective universe of discourse, but we kept the same five levels for the final output (resilience, fragility and aggravation). We think that 3 classes is enough to represent accurately the input variables of the resilience and fragility models. Moreover, a reduction of the number of classes implies also a more compacted and reduced set of fuzzy rules. In the same way, to improve model's sensibility, we adjust membership functions forcing them to be more *data-based* kind of type, thus considering the reported aggravation data as embedded along membership functions limits definition. With these new membership functions we build a set of fuzzy logic rules that could infer the behaviour of the aggravation coefficient components using the three Mamdani Fuzzy Inferences Systems mentioned before (see Figure 2).

The developing of the fuzzy rules was established for consider all possible combinations between the input descriptor's linguistic levels, giving a total of

Table 2: Logic Rules used for resilience estimation. HHR=Human Health Resources, DL= Development Level, EO=Emergency Operability, R = Resilience, VH = Very High, H = High, M = Medium, L= low, VL = Very Low

1. If (HHR is L) and (DL is L) and (EO is L) then (R is VL)
2. If (HHR is M) and (DL is M) and (EO is M) then (R is M)
3. If (HHR is H) and (DL is H) and (EO is H) then (R is VH)
4. If (HHR is M) and (DL is L) and (EO is L) then (R is L)
5. If (HHR is H) and (DL is H) and (EO is L) then (R is M)
6. If (HHR is L) and (DL is M) and (EO is L) then (R is L)
7. If (HHR is M) and (DL is M) and (EO is L) then (R is M)
8. If (HHR is H) and (DL is M) and (EO is L) then (R is H)
9. If (HHR is L) and (DL is H) and (EO is L) then (R is M)
10. If (HHR is M) and (DL is H) and (EO is L) then (R is M)
11. If (HHR is H) and (DL is H) and (EO is L) then (R is H)
12. If (HHR is L) and (DL is L) and (EO is M) then (R is L)
13. If (HHR is M) and (DL is L) and (EO is M) then (R is M)
14. If (HHR is H) and (DL is L) and (EO is M) then (R is H)
15. If (HHR is L) and (DL is M) and (EO is M) then (R is M)
16. If (HHR is H) and (DL is M) and (EO is M) then (R is H)
17. If (HHR is L) and (DL is H) and (EO is M) then (R is M)
18. If (HHR is M) and (DL is H) and (EO is M) then (R is H)
19. If (HHR is H) and (DL is H) and (EO is M) then (R is H)
20. If (HHR is L) and (DL is L) and (EO is H) then (R is M)
21. If (HHR is M) and (DL is L) and (EO is H) then (R is H)
22. If (HHR is H) and (DL is L) and (EO is L) then (R is H)
23. If (HHR is L) and (DL is M) and (EO is H) then (R is H)
24. If (HHR is M) and (DL is M) and (EO is H) then (R is VH)
25. If (HHR is H) and (DL is M) and (EO is H) then ((R is VH)
26. If (HHR is L) and (DL is H) and (EO is H) then (R is H)
27. If (HHR is M) and (DL is H) and (EO is H) then (R is VH)

27 rules for calculating fragility and resilience values respectively. The rules were intended to follow risk management literature which could suggest possible outcomes when three of these elements interact to form resilience or fragility. The Mamdani aggravation model, that has as input variables the resilience and the fragility, discretized into 5 classes each, is composed of 25 fuzzy rules. In Table 2 the rules of the Mamdani resilience model are presented as an example. As mentioned before, the use of classical fuzzy systems, with well established fuzzy inference theory, allow a high level understandability model, easily understandable by experts which leads towards a deepest discussion in the topic of social vulnerability description and casual interrelation.

Let's describe the inference process by following the example of the proposed Resilience FIS. The fuzzy inference engine combines the fuzzy *if-then* rules (see Table 2) into a mapping from fuzzy sets in the input space $U \subset R^n$ to fuzzy sets in the output space $V \subset R$, based on fuzzy logic principles.

Let's $U = U_1 \ x \ U_2 \ x \ U_3 \subset R^n$ and $V \subset R$, where U_1, U_2 and U_3 represents the universes of discurse of Marginal Slums, Social Disparity Index and Population Density input variables, respectively, and V the universe of discourse of Resilience. In hour case each input variable contains three fuzzy sets and the output variable is discretized into five fuzzy sets. Then, the fuzzy rule based shown in Table 2 can be expresed in a canonical form as shown in Equation 4.

$$R^{(l)} : IF x_1 is A_1^l and ... and x_n is A_n^l THEN y is B^l \tag{4}$$

where A_1^l and B^l are fuzzy sets in U_i and V, respectively, $x = (x_1,\ x_2,\ x_3) \in U$ are Marginal Slums, Social Disparity Index and Population Density linguistic variables, $y \in V$ is the Resilience linguistic variable and $l = 1, 2, ..., 27$ is the rule number. Consider now the fuzzy facts: x_1 is A'_1, x_2 is A'_2, x_3 is A'_3, being A'_1, A'_2 and A'_3 fuzzy sets.

The Generalized Modus Ponens allows the deduction of the fuzzy fact y is B' by using the compositional rule of inference (CRI), defined trough the fuzzy relation between x and y, as defined in Equation 5.

$$B' = A' \circ R \tag{5}$$

where $A' = (A'_1, A'_2, A'_3)$. The simplest expression of the compositional rule of inference can be written as Equation 6.

$$\mu_{B'^i}(y) = I\left(\mu_{A^i}(x_0), \mu_{B^i}(y)\right) \tag{6}$$

when applied to the ith-rule; where:

$$\mu_{A^i}(x_o) = T\left(\mu_{A_1^i}(x_1), \mu_{A_2^i}(x_2), \mu_{A_3^i}(x_3)\right)$$

where $x_0 = (x_1, x_2, x_3)$. Here, T is a fuzzy conjuctive operator and I is a fuzzy implicator operator.

Once the inference is perfromed by means of the compositional rule of inference scheme, the resulting individual (one for each rule) output fuzzy sets are aggregated into an overall fuzzy set by means of a fuzzy aggregation operator and then a defuzzification method is employed to transform the fuzzy set into a crisp output value, i.e. the resilience level following the example. The defuzzification method used in this work is the Centre Of Gravity (COG), which slices the overall fuzzy set obtained in the inference process into two equal masses. The centre of gravity can be expressed as Equation 7.

$$COG = \frac{\int_a^b x\mu_B(x)dx}{\int_a^b \mu_B(x)dx} \tag{7}$$

where B is fuzzy set on the interval $[a, b]$.

In this research, this Mamdani fuzzy inference process is used for both descriptors, i.e. fragility and resilience. Once the evaluation has been made for both descriptors, it's possible to calculate the aggravation coefficient using the Aggravation fuzzy inference system (see Figure 2). The antecedents in this case are the resilience and fragility descriptors and the consequent is the aggravation coefficient. The crisp value for the aggravation coefficient was obtained also trough the calculation of COG. For comparison purposes and following Carreño's fuzzy previous work, the obtained aggravation value is then used to evaluate aggravation's linguistic level, in order to perform a graphical representation of the levels of aggravation in each district, as presented in the next section.

In absence of a defensible method for assigning weights for social vulnerability estimators (Cutter, 2003), and contrarily to Carreño's fuzzy approach, we did not made any a priori assumption about the importance of each factor in the overall behaviour of the system. In this way, each factor was viewed as having an equal contribution to the fragility or resilience configuration. In this way it becomes possible to study the importance of the weights assigned in previous works when evaluating an aggravation coefficient.

4 RESULTS AND COMPARISON

Figure 3 shows the estimated spatial distribution of the aggravation coefficient and its correspondent level for the 10 administrative districts, of the city of Barcelona, achieved through the proposed model. Figures 4 and 5 show the aggravation coefficient calculated by Carreño et al. using fuzzy sets or index methods, respectively.

The proposed model, equal than the two alternative methods, estimates that highest aggravation is spread mostly over the northeast part of the city. In our model, levels of *very high* are reached over Sant Martí and Nou Barris district, *high* for San Andreu, *medium-high* values for Horta-Guinardó and Ciutat Vella, while the rest of the city presents values of *medium-low* aggravation level.

As we can see in Figure 4, Carreño's fuzzy method considers that most of the city aggravation coefficient ranges between *medium-low* and *medium-high* levels, while index method and our proposed method resemble similar value levels (*medium-low*) thus not overestimating aggravation.

Figures 6, 7 and 8 show the aggravation coefficient numerical value obtained by the proposed fuzzy model, the index model and Carreño's fuzzy model, respectively. Districts are ordered from lower to highest aggravation level. In these figures we can see that even there is no correct total match among the three methods, all of them preserve quite the same order in terms on higher and lower aggravation levels. When comparing the numerical aggravation value obtained from both fuzzy models (Carreño's fuzzy model and the proposed model) to a robust method like index

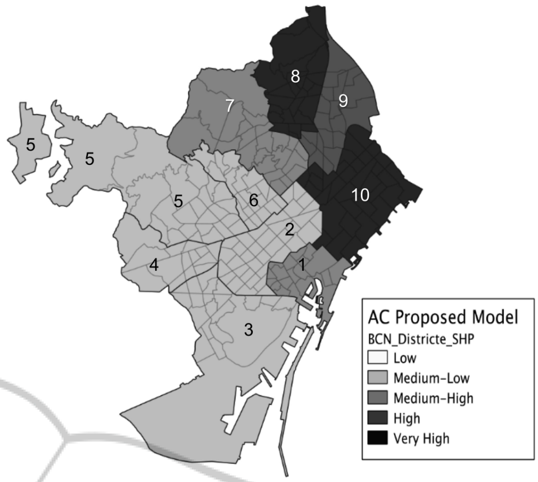

Figure 3: Aggravation Coefficient. Proposed Model: (1) Ciutat Vella, (2) Eixample, (3) Sants-Montjuic, (4) Les Corts, (5) Sarrià-Sant Gervasi, (6) Gràcia, (7) Horta-Guinardó, (8) Nou Barris, (9) Sant Andreu, (10) Sant Martí.

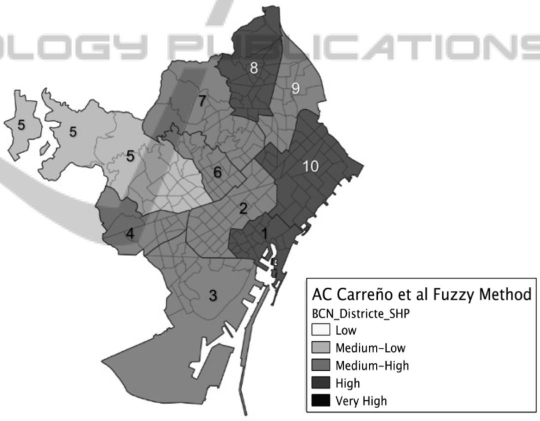

Figure 4: Aggravation Coefficient. Carreño *et al* fuzzy method: (1) Ciutat Vella, (2) Eixample, (3) Sants-Montjuic, (4) Les Corts, (5) Sarrià-Sant Gervasi, (6) Gràcia, (7) Horta-Guinardó, (8) Nou Barris, (9) Sant Andreu, (10) Sant Martí.

models (Marulanda et al., 2009), both suffer a slight under and overestimation of the aggravation values by district. In the proposed method this issue could be addressed with the inclusion of weights to each descriptor, as the other methods do. Nevertheless, we consider that even with these small numerical dissimilarities, the proposed fuzzy model limits the different aggravation levels in a suitable way, allowing the identification of more potentially problematic zones with a good resolution and reduced computation time.

Figure 9 shows the same as Figures 6, 7 and 8 but without ordering the districts by aggravation value, showing how the aggravation values behaves along the different districts. As it can bee seen, even if the explicit aggravation coefficient value is not the same

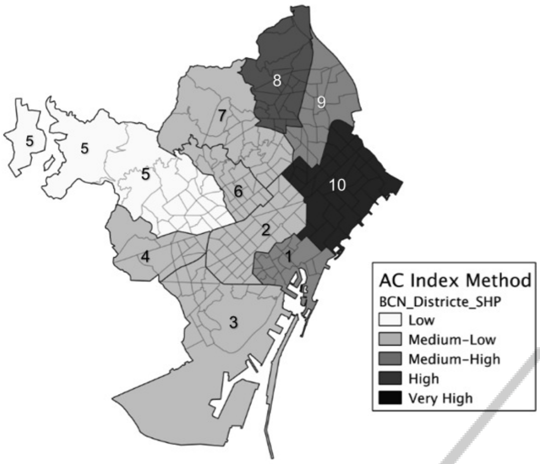

Figure 5: Aggravation Coefficient. Index Method: (1) Ciutat Vella, (2) Eixample, (3) Sants-Montjuic, (4) Les Corts, (5) Sarrià-Sant Gervasi, (6) Gràcia, (7) Horta-Guinardó, (8) Nou Barris, (9) Sant Andreu, (10) Sant Martí.

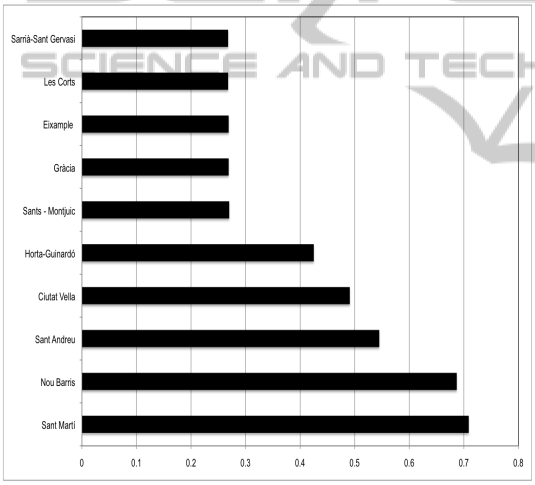

Figure 6: Aggravation Coefficient values by district, Proposed Fuzzy Model.

for each district, a similar trend shape come to appears (with the inherent over and underestimation aggravation level), which leads to the conclusion that the general behaviour of the proposed model is coherent with the other two mentioned models.

4.1 Discussion

According to the previous analysis, with the use of classical fuzzy inference system methodology it is plausible to reproduce the results obtained from a more analytical method such as indexes, for example: in terms of district aggravation classification, or in reproducing similar spatial pattern of aggravation. In first term, the proposed inference model allows a useful simplification for the large quantity of variables required for social aggravation analysis, in the spirit of reduce the subjectivity associated with aggravation descriptors suitability designation by using a more flexible and small descriptors set in which the underlying links between them can be more easily observed, enabling a more understandable analysis scheme for social aggravation inference estimation. Building rules directly over the aggravation descriptors allows to assemble a compositional rule of inference over the very same descriptors that are assumed to create aggravation itself, therefore the inference process can be made using rules designed to follow risk management knowledge, allowing the model to represent, with a certain degree of freedom, the actual understanding of aggravation formation, and at the same time, it allows a real discussion of the rule's structure strength; which can be absolutely improved with a deepest debate.

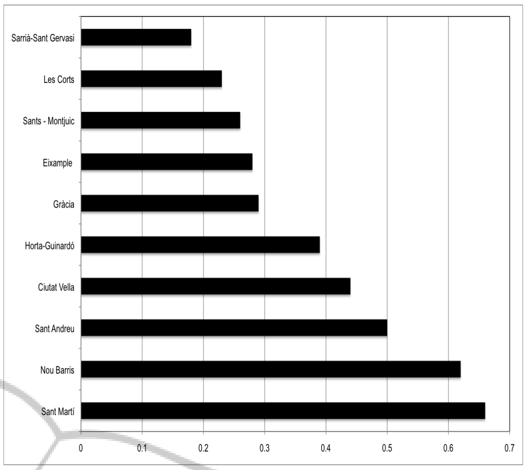

Figure 7: Aggravation Coefficient values by district, Index Model.

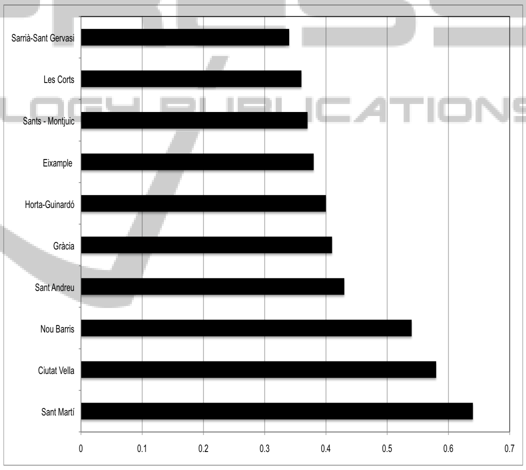

Figure 8: Aggravation Coefficient values by district, Carreño's Fuzzy Model.

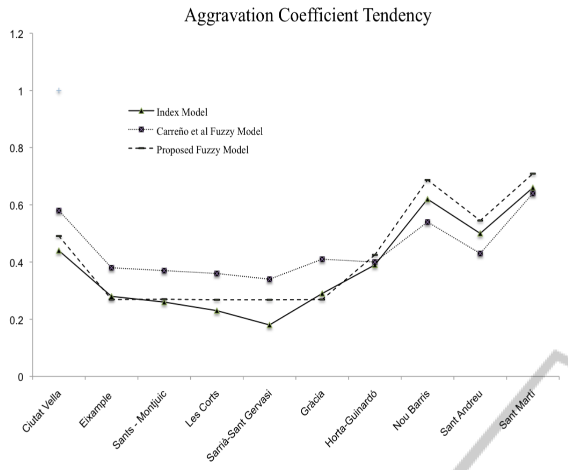

Figure 9: Aggravation coefficient comparison over the 10 Barcelona Districts.

Fuzzy logic inference capabilities can be exploited in a more suitable way because the outputs from each FIS used in the model are always fuzzy sets, giving the chance to connect them trough a new FIS without loosing consistency, allowing model completeness.

At the other hand, the proposed model slightly over and underestimated aggravation values for some districts when comparing with index model, as it is also de case of Carrenõ's fuzzy model. However, if necessary, the proposed fuzzy model can be further tuned if descriptors are weighted.

4.2 Future Work

The flexibility of the model enables its adaptation to several conditions which could be used in more general studies of social vulnerability and that can also help to fill some gaps among analytic methods. For example, the same procedure can be applied to a more general social vulnerability model that considers not only physical, and aggravation inputs, but environmental, economic and even completely subjective descriptors can be add as well, such as solidarity or brotherhood [2]. All of these can then be embedded into one single inference model. One of the main problems of risk ex-ante and ex-post models is that they don't necessarily consider the interconnectivity of social characters (sectors) in a real scenario, for example, the lack of hospitals in one geographic area does not necessarily mean that human health resources is zero at that place. It will be like assuming that the fire department can only help those who are in close proximity. Assuming interconnectivity, the potential damage to the social network-connections in case of disaster is the real issue that must be addressed, and we consider it plausible to be approach using fuzzy methods.

[2]Loosing in this way its event-base model characterization.

5 CONCLUSIONS

We obtain a inference fuzzy model to make an estimation of social aggravation over Barcelona city using the descriptors proposed in (Carreño et al., 2012). Building inference compositional rules over the selected descriptors, we were able to obtain a robust method that resembles the identification of relevant aspects and characteristics of seismic risk of cities already achieved by two other consolidated methods. The proposed model displays more simplicity, flexibility and resolution capacities and can be rapidly transformed into a non-disaster event model type with the inclusion of new type of variables, englobing a more detailed social vulnerability scheme and interconnectivity issues.

REFERENCES

Cutter, S. L., Boruff, B. J., Shirley, W. L., (2003) Social Vulnerability to Environmental Hazards. *Social Science Quarterly*,84.

Cardona, O. D., (2001), Holistic evaluation of the seismic risk using complex dynamic systems (in Spanish), *PhD Thesis* Technical University of Catalonia, Barcelona, Spain.

Cardona, O. D., (2003), The need for rethinking the concepts of Vulnerability and Risk from an Hollistic Perspective: a necessary review a criticism for effective Risk Management, *Mapping Vulnerability: Disasters, Developing and People* Chapter 3 Earthscan Publishers, London.

Carreño, M. L., Cardona, O. D., Barbat, A. H., (2007), Disaster risk management performance index, *Nat Hazards* 40 1-20.

Carreño, M. L., Cardona, O. D., Barbat, A. H., (2012) New methodology for urban seismic risk assessment from a holistic perspective *Bull Earthquake Eng*, 10, 547-565.

Mamdani, E. H., Assilian, S., (1975) An experiment in linguistic synthesis with a fuzzy logic controller. *Intern. J. of Man-Machine Studies*,7(1), 1-13.

Marulanda, M. C., Cardona, O. D., Barbat, A. H., (2009) Robustness of the holistic seismic risk evaluation in urban centers using the USRi, *Nat Hazards*, 49, 501-516.

Kumpulainen, K., (2006) Vulnerability Concepts in Hazard and Risk Assessment *Geological Survey of Findand*, 42, 65-74.

Saaty, T. L., Vargas, L. G., (1991) Prediction, projection, and forecasting: applications of the analytical hierarchy process in economics, finance, politics, games, and sports, *Kluwer Academic Publishers*