Bird's Eye View to Indonesian Mass Conflict

Revisiting the Fact of Self-Organized Criticality

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Abstract

The paper statistically observed the recorded data of the series of social clashes and violence in Ambon, Indonesia in the period of social conflict between 1999-2004. The scaling laws are revealed and the power-law fitting procedures and analysis are conducted. The results also reviewed some findings in wars among countries in the worlds now well known as Richardson's Law. The paper also discussed the plausible explanations in the sense of possible underlying process of the famous self-organized criticality by reviewing the classic forest fire model. Some further sociological explorations in the sense of computational and agent-based model approaches are also conjectured.

Keywords: social clashes, social conflict and violence, power law distribution, Richardson's Law, self-organized criticality.

1. On Mass Conflict

By the years after the fall of the New Order regime in the period of social transformation to the politically reformed era, Indonesia has witnessed many civil wars among its people respect to various issues driven them (religious or ethnic ones) and broad impacts to the national strength; apparently with distinctive numbers of casualties and severances must be paid (Sihbudi, *et. al.,* 2001). Nonetheless, practically speaking, the events of social conflict or civil violence are never too easy to analyze since any social movements at the occurrences of the conflicts were comprised by great deal of mixed and twisted issues and relevancies. Social mobilizations could be brought in to its highest escalation – turning out to be bloody and disruptive massive violence – not by solely one issue. The motives can be derived from a great deal of aspects, e.g.: social and economic hardships, social clusters and gaps, the lack of widely accepted sovereign government or political regime, and a lot more roots of the social conflict (*cf.* Epstein, *et. al.*, 2001). Thus, the complexity of its nature makes the conflict resolution is never an easy task (*cf.* Woods, 2003).

However, generally speaking, civil violence is mostly related to the mass mobility regarding to certain collective identities among social actors (*cf.* Lustick, 2000 & Srbljinovic, *et. al*, 2003). This fact is quite obvious in some cases of mass violence in Indonesia and some other countries prone to conflict. This brings to the most conventional, yet powerful conflict resolution is by bridging the communications and continuously interactions between the conflicting sides and the role of legitimate each side's leaders is somehow important in order to maintain peace. Previously, we have tried to see the possible structure of the massive conflict by analytically laid the model in the occasions of mass mobility (Situngkir, 2003). Here, we would like to present a general approach that could possibly offer alternative explanations and understandings to the social conflict by observing some statistical properties of the empirical data we collected on Indonesian massive civil violence.

One of the biggest and severe massive civil violence was occurred in Ambon, Maluku[1]. At this particular case, the social mobilizations were basically recognized to be driven by the religious issue between those who were Christians and Muslims. This was one of the longest and most sophisticated civil conflict occurred in the country while in return sacrificed most human souls as it appeared to be one of the broadest social conflict and massive violence geographically.

A map regarding to the conflict in Ambon pointing the place of the mass mobilizations along with respective casualties are shown in figure [1]. From the figure we

[1] The data we use in this report is collected from many sources in the period of conflict in Ambon since 1999 to 2004. In fact, there is no exact numbers of the total casualties in Ambon Social Conflict. The long time conflict actually might have taken more than ten thousand of people (Crisis Centre Keuskupan Ambonia) or could also about 1900s people as reported by Tadjoeddin (2002). The data we used in the paper is compiled from the records of some different reliable sources. All used data is available upon request.

could see that the Ambon’s conflict took many places as it also took great number of casualties in the time of conflict and social mobilizations. From our database, the long time tragedy of the Ambon’s conflict was begun on January 1999 and it took place at places like Mardika, Sanana, Telaga Kodok and Benteng Karang, Waiheru, Kaimiri, Hilla Vilage, and Hunuth, all located in the Ambon Island and in the area of Ambon City (see fig. 1).

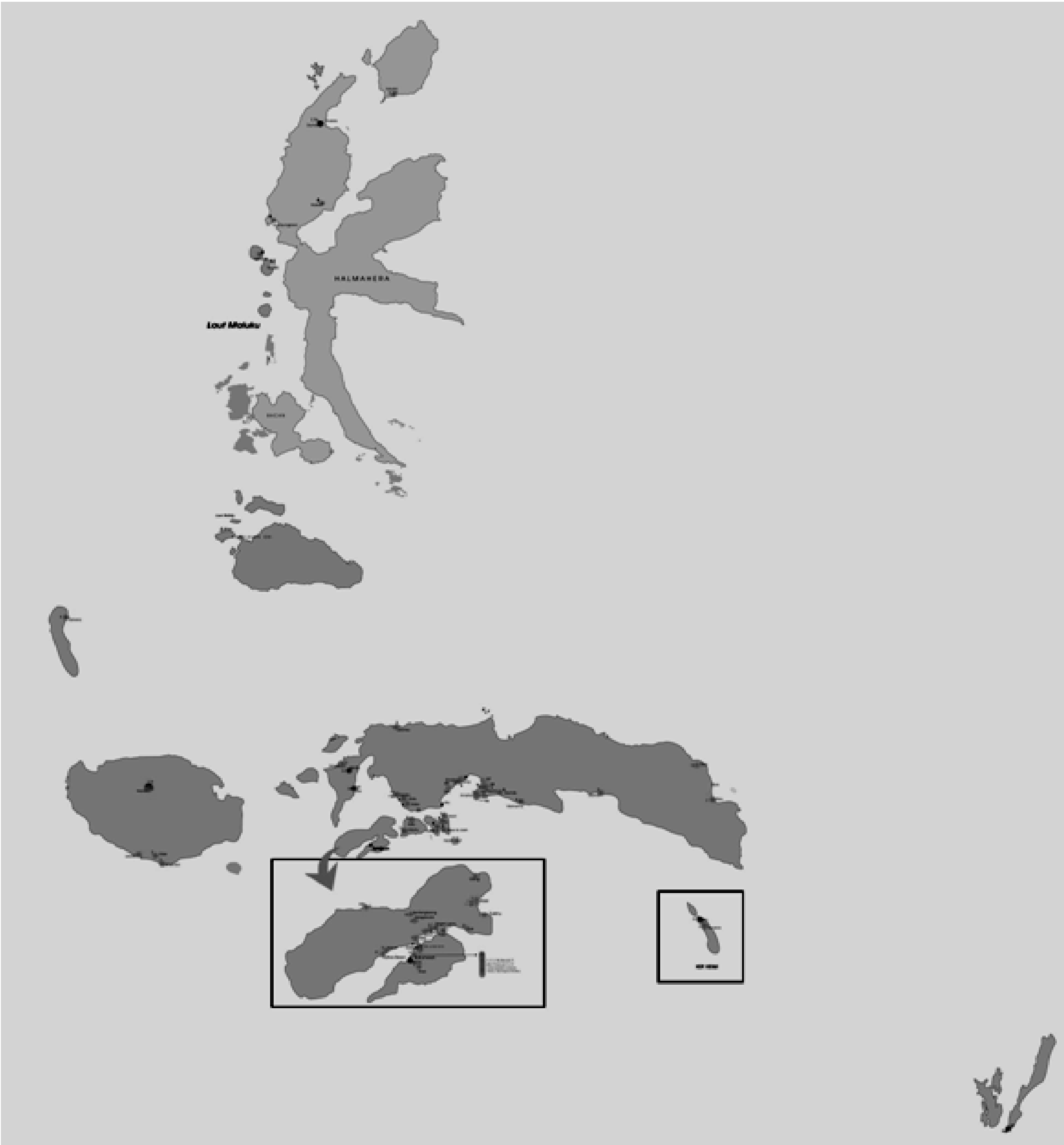

Figure 1. The geographical features of social conflict and civil violence in Maluku, Ambon (1999-2004)

The first clash had more than recorded twenty casualties and after that the conflict and “hatred” between the conflicting social identities seems to be contagious as the killings were spread throughout the Ambon islands. The quiet and peace suddenly had changed into the vigorous state of violence and people were got killed, houses were burnt, the city, business, and economic activities collapsed. The conflict seemed to be contagious even up to the northern islands in Halmahera.

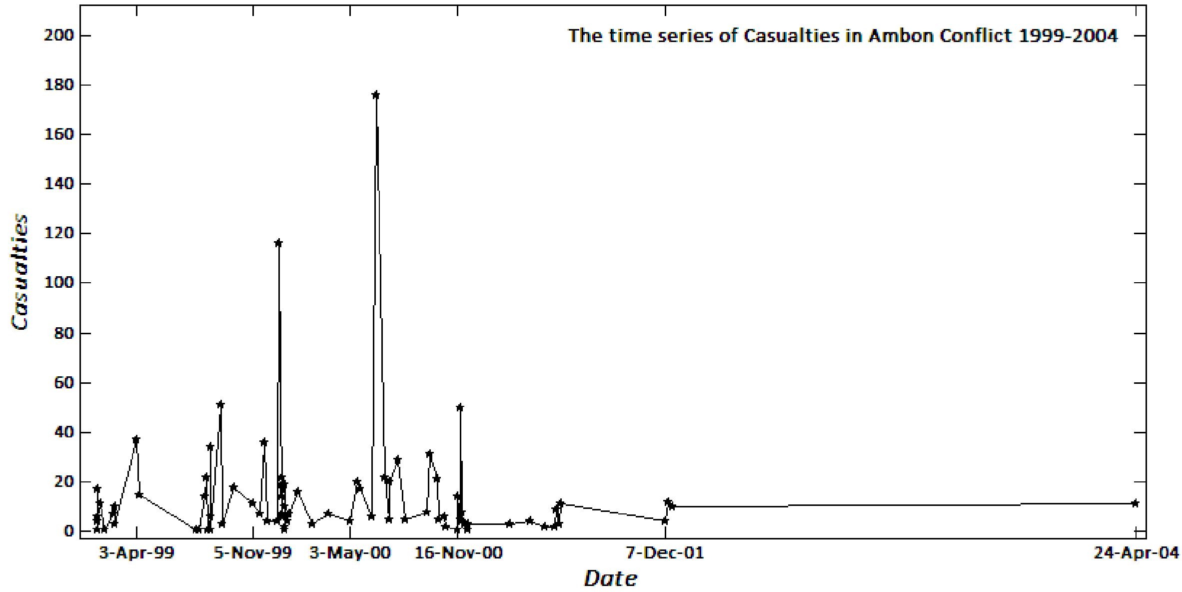

Figure 2. The casualties in the long time conflict in Ambon

2. On Power Law in the Mass Conflict's Casualties

Many analyses have been delivered in order to explain the massive conflict and civil violence and the motive of the paper is to bring a slightly different approach to the empirical data of the conflict while modestly trying to build an alternative possible explanations. Obviously, one important step to prevent more severances in conflict and violence is by understanding some properties of the conflict, be it from macro-views or the micro-states of social actors emerging the observable properties of the social system. This is what we want to present in the paper.

One of the interesting feature of the quantitative analysis on social conflict and wars – yet frequently overlooked and not frequently cited – were once introduced by English physicist and meteorologist, Lewis F. Richardson (1948). He showed that the sizes of war casualties in the world were following the simple multiplicative process, known as the power law. Richardson's calculations depicted that for each ten-fold increase in severity, the frequency decreased by somewhat less than a factor of three. An interesting and detailed quantitative approach was thus conducted by Cederman (2003) to see more theoretical implications of the revealed fact. This is an interesting fact for in some other cases, the power law has also been discussed to be present in a lot of other scientific domains and observations (*cf.* Situngkir, 2003 or the detail with various data in Newmann, 2005).

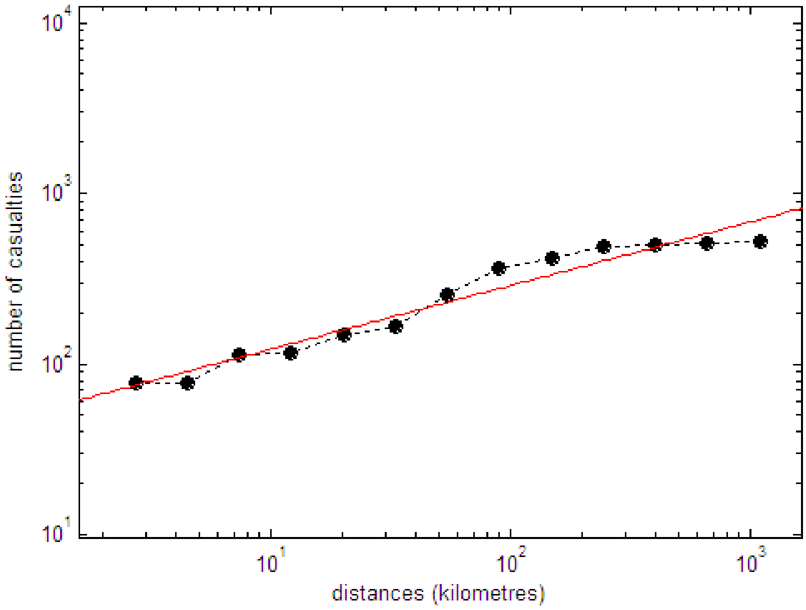

Figure 3. The scaling over logarithmic distance of Ambon's Conflict measured from the Ambon City 1999-2004

Like wars in the world, the most frequent facts to be observed in a massive conflict and civil wars are the death tolls. It is valid to simply said that the greater the casualties the greater the size of the civil war. Of course, the geographically impact of the conflict can also be seen as a measurement to the size of the war. Apparently, this is showed in figure [3]. It depicted the scaling properties of the number of killings by logarithmically measure the radius from the Ambon city to the places where the impact has taken other (and possibly bigger) casualties. This fact is interesting as one of the discussions in the following section later on the paper. Regarding to the figure [3], it is important to note that the displayed data points of each figure represent the averages over non-overlapping interval bin on the rank variable (*x*-axis) that is centered at the showing points. Here, the size of each bin is changing on every step in such a way to have the constant value in the logarithmic scale. The aim is of course to smooth the persisting fluctuations in the data in order to ease seeing the emerging pattern.

Probably the most interesting feature we could see in the mass conflict and also the main concern of our discussion is the presence of the power law distribution of the casualties of the civil war, reminding us to the discovery of Richardson (1948). As it has been discussed in Newman (2003), and with particular themes in Moura, *et. al.* (2006) as well as in Situngkir (2007), we denote $p(x)$ as the probability density function for the data or statistical event of x and it follows power law of,

$$p(x) = \frac{A}{x^{\alpha}}, \qquad (1)$$

consequently, $p(x)dx$ denotes the fraction of the conflict event with casualties in the interval of $[x, x+dx]$. Thus, we can write down the cumulative distribution function – as the probability of a certain statistical event in the death toll of which certain number of victims equals to or greater than x - that also follows the power law

$$P(x) = \int_x^\infty p(x')dx' = \frac{Ax^{-(\alpha-1)}}{(\alpha-1)} + c \qquad (2)$$

However, we understood that not all of the data in the data distribution fulfills the power-law (Newman, 2005). By observing the equation (2) above, we understood that in the cumulative distribution function, there would be such $x_{\min}$ that would make the distribution of the data become able to be normalized as,

$$1 = \int_{x_{\min}}^\infty p(x)dx = A\int_{x_{\min}}^\infty x^{-\alpha}dx = \frac{A}{(1-\alpha)} x^{-(1-\alpha)}\Big|_{x_{\min}}^\infty \qquad (3)$$

and this become the main reason for the power laws would generally fulfils $\alpha > 1$. Apparently, the value of $x_{\min}$ is not necessarily the minimum number in our data set but the minimum value for the data fulfils the power law. Hence, we have the normalized expression of for the power law becomes

$$p(x) = \frac{(\alpha-1)}{x_{\min}}\left(\frac{x}{x_{\min}}\right)^{-\alpha} \qquad (4)$$

In our fitting processes to the distribution of the data, we use the value of X_{min} = 9.9623 that is the value with which the data $x \geq x_{\min}$ comply the power law.

Furthermore, as we always fit the power-law distributed data better in the logarithmic axes, usually we found the data fluctuates in large values in the tail of the distribution. In order to avoid the difficulties may arise in the fitting process, we reduce the fluctuation by using the logarithmic binning so that bins of the data span at increasingly larger intervals exponentially (e^i where i denotes the iterative numbers).

In our analysis we use two methods of fitting processes. The first is the maximum likelihood estimator (MLE) as introduced and derived in Newman (2005),

$$\alpha = 1 + n\left[\sum_{i=1}^{n} \ln\frac{x_i}{x_{\min}}\right]^{-1} \qquad (5)$$

where n is the number of the data, and x_{min} the practical minimum value for the data points x_i follows the power law as discussed previously. Furthermore, the estimate of the expected statistical error σ is given by

$$\sigma = \sqrt{n}\left[\sum_{i=1}^{n} \ln\frac{x_i}{x_{\min}}\right]^{-1} = \frac{\alpha - 1}{\sqrt{n}} \tag{6}$$

In the other hand, we also use the method of fitting is the standard method of Least Squares Fitting (LSF) in the log-log scale of the data points as a comparative.

Table 1. The fitting with MSE and LSE method.

	α
MSE	2.3176 ± 0.3196
LSF	2.0827

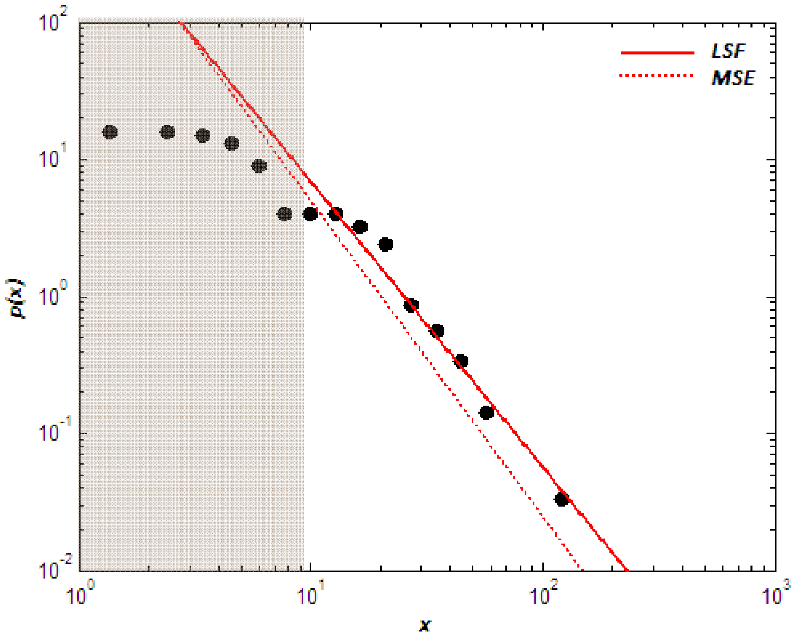

Figure 4. The power-law in the distribution of the casualties in Ambon Conflict 1999-2004. The shaded area is the part of the data not included in fitting process as we use the value of X_{min} = 9.9623.

The result of the fitting process is shown in table 1 and figure [4]. In order to confirm more about the power law, it is also shown in figure [5] the fitting value of the distribution function with the real data. It is obvious that the data is attracted to the power law fitting line of those variables we calculated.

As it has been observed by Moura, *et. al.* (2006), in general, the fitting exponent by using the MSE is bigger than the one resulting from the LSF method. However, our main concern is that by using both fitting methods, we found that the power law exponent is approximately ≈ 2 with good fitting result ($R = 0.9836$).This fact interestingly confirms the Richardson law, that the power law is also appeared in the local wars – not only within the wars of the world. There have been such micro processes in the social system that emerged the bird's eye view of this interesting statistical feature. However, our discussions would eventually approach possible micro process in civil violence or local massive conflict (that is related to certain collective identities) yielding such multiplicative process of the casualties.

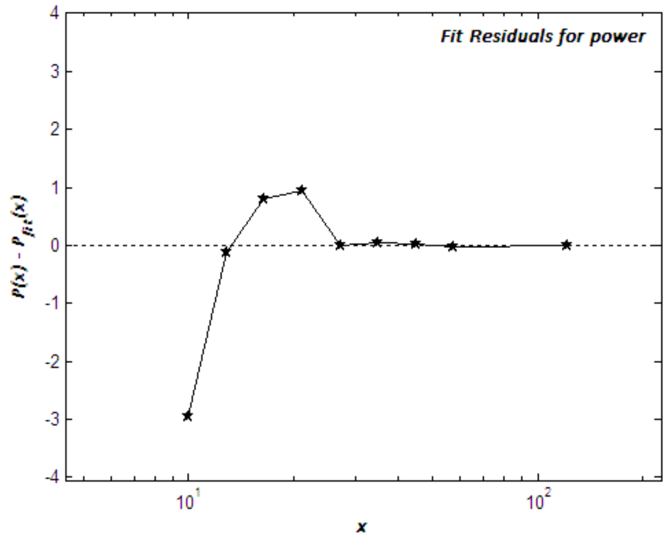

Figure 5. The power-law fit residuals.

Interesting statistical facts from this finding are however the value of the moments since power laws always bring non-statistical Gaussian properties. Since the exponent is $2 < \alpha < 3$ we can say that the first statistical moment (mean) does not diverge as if $\alpha = 1$. The value of $\mu = < x >$ would settle down to a finite value in the limit of large data set. We can write down the value of the first moment as

$$< x >= \int_{x_{\min}}^{\infty} xp(x)dx = A\int_{x_{\min}}^{\infty} \frac{x}{x^{\alpha}}dx = -\frac{A}{\alpha - 2}x^{-(\alpha-2)}\Big|_{x_{\min}}^{\infty} = \frac{(\alpha - 1)}{(\alpha - 2)}x_{\min} \qquad (7)$$

However, the second moment (mean square) can be written as

$$< x^2 >= \int_{x_{\min}}^{\infty} x^2 p(x)dx = A\int_{x_{\min}}^{\infty} \frac{x^2}{x^{\alpha}}dx = -\frac{A}{(\alpha - 3)}x^{-(\alpha-3)}\Big|_{x_{\min}}^{\infty} \qquad (8)$$

and reading the findings of the fitted exponent, we could say that the second moment of the data would diverge in infinite value as the data set is larger. This is interesting feature though, for theoretically speaking the ranges of the possible number of casualties in any social clashes become ill-defined as we draw more and more samples into infinity.

Furthermore, from the derivation of Newman (2005), we could see that the theoretical largest value with this interval of power law exponent,

$$< x_{\max} > \sim n^{\beta} \quad (9)$$

where

$$\beta = \frac{1}{(\alpha - 1)} \quad (10)$$

and theoretically we can say that the possible largest value of the casualties could always increases in the limit of largest sample size.

3. Discussions: Self-Organization Criticality in Social Conflict and Massive Violence

Finally we arrive to the possible theoretical discussion based upon the question of what we can learn from the findings of the power law in this specific Indonesian social conflict. The notion of the self-organized criticality has been proposed in Cederman (2003) that brought to us the consequence of the self-organized criticality system where the steady linear input generates tensions inside the system that in turn lead to non-linear and delayed output ranging from small events to huge ones (Bak, 1996). In return, theoretically speaking the social conflict could also features the strong degree of path dependence - the very sensitive macro system to the initial conditions of the social system, or roughly speaking the historical pathways from micro to macro properties of the system.

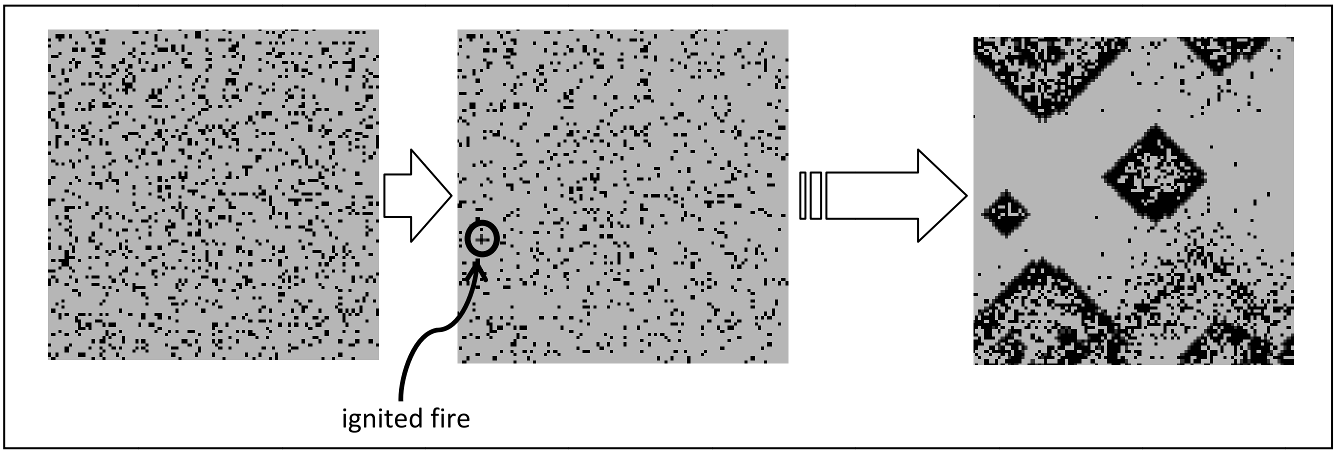

Figure 6. A running computational simulation of the classic forest fire model showing the self-organized criticality could be an interesting analogical model to the conflict since the size of the fire emerging the power law distribution (*cf.* Drossel & Schwabl, 1992 and Turcotte, 1999)

That is probably why – as we have noted in the beginning of the paper – the massive conflict and violence seemingly always brings surprise and sudden (felt) effect from the peace to disrupting and harsh situations. Nonetheless, of course in the case of massive conflict there are no regularities at all as in chaotic system (*cf.* Situngkir, 2002). A conjecture to this theoretical understanding, however, has brought us to the discussions of the complex social system as it has begun in our previous work (*cf.* Situngkir, 2004) – for instance, the use of computational simulations to see the pattern as it is emerged in the sense of micro-macro linkage. These regularities of social conflict can be observed from the pattern of the tensions among the different collective identities interacting in the social system (*cf.* Lustick, 2000), the dynamics of the mass mobility (*cf.* Srbljinovic, *et. al.*, 2003) or possibly the unmatched settlements among the conflicting sides (*cf.* Woods, 2002).

An interesting possible qualitative and theoretical analogy could be plausible to describe the massive conflict as it has occurred in several places in the country – and in our cases the social conflict in Ambon (1999-2004). Imagine we have a forest with some percolations (Reynolds, *et. al.*, 1977) among them which somewhat is also showing the size of "population" distribution that also emerging the power law (Moura, 2006). A lightning strikes and ignites a fire on one particular tree. Then the fire spreads in the adjacent trees within certain percolations, and so on. This brings any possibilities of the ignited fire till eventually there would be some places in the forest with the burning trees with apparently different sizes. As it has been showed in Drossel & Schwabl (1992), the cumulative distribution of the fired trees in some values of the computational simulations (see figure [6]) would also yielding the power law. Turcotte (1999) used this as an exemplification of the used analogy of the self-organized criticality to explain the Richardson's (power) law. The plausibility of the analogy can be brought from the power-law distributed of the initial percolations (since there are empirical findings of the power law distributed population in cities and municipalities) and the sizes of the fire could represent the sizes of the social clashes as measured in the sizes of the death tolls. Since both macro properties in social system and in forest fire model are organically settled, thus both could be interestingly similar: showing the process of self-organized criticality. Properties of percolations, sudden clashes lead to massive violence, and so on, have been depicted in figures [1], [2], and [3] at the previous sections.

However, although there is no theoretical guarantee that the presence of the power law distribution always represents the self-organized criticality as the underlying processes, the computational frameworks as referred above along with our understanding on the self-organized criticality could be useful to (at least) intuitively observing the percolations of organic residences, populations, cities and municipalities to find a way in the practical effort inhibiting the spreading of the conflict. The analogy of the forest fire model might not plausible enough to explain sizes of wars as pointed out by Cederman's (2003) caveats and proposal of new model explaining the sizes of war. However, by distinguishing war among countries as not merely and organically as the massive conflict among civilians in bounded regions; the analogy of the self-organized criticality depicted in the forest fire model might become more suitable explaining the statistical feature we presented in the previous section. Yet, further endeavors on this becomes a challenging further works to build a more plausible computational model in sociological analysis of massive conflict and violence among civilians regarding micro properties that driven the clashing individuals or social groups and identities.

4. Closing Remarks

We show the scaling properties in the empirical data of social conflict occurred in Indonesia, i.e.: series of social clashes in Maluku, Ambon that was probably one of the most frightening social circumstances recently in the country. We also fit the distribution of the sizes of the conflict measured by the numbers of the casualties in the recorded series of the massive contacts between 1999 until 2004. The discussion has brought us to observe some interesting statistical features depicted from the fitting process. As the power law distribution reminds us to the classical work known today as Richardson's Law, we review the plausibility to see the social clashes in the terms of self-organized criticality. Furthermore, the discussions distinguish the model that could be used to explain wars in the world with those driven by social motives and organically spreading clashes leading to massive violence.

The paper reviews the further the classic model of forest fire that can be used as an intuitive analogy with the social clashes. However, it is worth to note and emphasize that there is always a possibility that the underlying process is much more complex than the in the forest fire model. The pioneered computational works incorporating agent based model and the emergence of micro-macro linkage on this particular issue have also reviewed and referred for more advanced and detailed description on explaining the social conflict and civil violence altogether with the most important works on how to manage and thus inhibit the spreading conflict or in the long term scientific endeavors for building the possible early warning system for social clashes. Apparently this is left to the further challenging works in computational sociology since this paper is modestly just giving glance of the bird's eye view of the social clashes occurred.

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Used Data are Compiled from:

Sala Wuku Foundation. URL: http://www.fica.org/hr

Tempo Magazine Online. URL: http:www.tempointeraktif.com

Lintas Peristiwa Kerusuhan di Maluku 1999 s/d 2001. Crisis Centre Keuskupan Ambonia. URL: http:websitescrg.com/ambon/index.htm#/Articles

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