

Conflict Prediction Model in a Dynamic State

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ABSTRACT

Environmental conflicts arise as a consequence of actions preventing or compelling some outcome at the resistance to the actions. More specifically, they are caused by anthropogenic activities that strain and damage the environment. Modelling environmental conflict is one of the fundamental ways providing means of solving them. In order to understand and model them, it is critical to identify potential and/or existing conflict causes (structural causes or proximate causes), as well as possible factors contributing to peace. In this paper, the dynamic time varying model for predicting environmental conflict is developed using Bayesian theory. The initial (state) conditions which play a significant role in the success of conflict resolution are estimated through a logistic probability model. An analogy on the application of the model in modelling of environmentally-induced conflict is given.

Key words

*Bayesian rule, environmental Conflict, dynamic state, initial conditions, Logistic probability model, Ultimatum game,

Introduction

Environmental or any other conflicts arise due to a condition in which actions of one person prevent or compel some outcome at the resistance of the other. Quite often this may result in “two or more competing, often incompatible, responses to same event” Omwenga and Mwita (2010). In the recent past, formal models and quantitative analysis have come a long way towards explaining how strategic actors bargain in a variety of conflict

settings. For instance, in the political setting or international relations, bargaining plays a central role in understanding and solving any conflict and thus, the mastery of the concept of bargaining is very important; Banks (1990), Huth and Allee (2002), London (2002), Powell(1987, 1996).

To understand the basics of the logic of bargaining in the face of conflicting interests, Game Theory has played a key role. For instance, political scientist have employed for

instance, bargaining models to analyze effects of open and closed rules on the distributive politics of legislative appropriation to the study of war initiation and termination; Baron and Ferejohn (1989), Mansfield et al. (2000).

Most environmental based conflicts are triggered by the differences in opinions and interpretation of ideas. It is therefore important that these differences are understood in terms of their magnitude in a conflict and taken care of before any bargaining can commence. This gives the opinion of each party an unbiased attention, since they fairly assign time/attention based on their contribution in a conflict. Further, theoretical studies of the bargaining problem have pointed to the importance of asymmetric information and the “reservation values” (control variables) of players in distributional conflicts. In general, it is important to understand the effects of control variables on the bargaining process.

Conflict situations can be described by statistical and numerical models of the system dynamics. These models rely on fundamental or empirical models that are frequently described by systems of ordinary differential equations (ODEs), Signorino (1999, 2000). The models can be used to predict the future behaviour/dynamics of any environmental based conflict, provided that the initial states of the conflict are known or can be estimated.

In order to understand and model a given environmental conflict, it is fundamental to identify potential or existing conflict causes, as well as possible factors contributing to peace. The causes of conflicts can be described as those factors which contribute to people’s grievances and can be categorised as: Structural causes – pervasive factors that have become built into the policies, structures and fabric of a society and may create the pre-conditions for violent conflict, Proximate causes – factors contributing to a climate conducive to violent conflict or its further escalation, sometimes apparently symptomatic of a deeper problem, Triggers – single key acts, events, or their anticipation that will set off or escalate violent conflict. Other factors like protracted conflicts also tend to generate new causes (e.g weapons circulation, war economy, culture of violence), which help to prolong them further.

As the main causes and factors contributing to conflict and to peace are identified, it is important to acknowledge that conflicts are multi-dimensional and multi-causal phenomena – that there is no single cause of conflict. It is also essential to establish linkages and synergies between causes and factors, in order to identify potential areas for intervention and further prioritise them.

Various accounts on the modelling of a conflict from the perspective of social welfare theory and social choice theory have been given by Gordon (2007). Complete data

defining all of the states of a conflict system at a specific time are, however, rarely available. For instance, in a conflict, for instance, there are some underlying issues that can be described to be private and as such may not be available. This challenge can however, be handled using missing data analysis techniques, Rubin (1996), Harzog and Rubin (1993). Moreover, both the models and the available initial data contain inaccuracies and random noise that can lead to significant differences between the predicted states of the system and the actual states of the system. In such a case, observations of the system over time can be incorporated into the model equations to derive improved estimates of the states and also to provide information about the uncertainty in the estimates.

In this paper, we present a model for conflict prediction in a dynamic state based on the state dynamics as represented by the ordinary differential equations (ODEs). Critical to the conflict prediction model are the initial conditions estimation. These initial conditions are estimated from the exponential state dynamic models by solving the model using Laplace transformation.

1.1. Exponential model

The dynamics in this case can be modelled by

$$\frac{dy}{dt} = \phi y, \quad y(0) = \theta, \quad (1)$$

where ϕ is representative for exponential growth rate of a conflict and y is a reducing

factor depending on the prevailing environmental factors.

But due to the in-deterministic nature of the environmental factors, y might remain missing. To overcome this, we propose a logistic model that takes care of the environmental dynamics given by,

$$\frac{dy}{dt} = \phi y \left(1 - \frac{y}{y_t} \right), \quad (2)$$

where y_t is the threshold values for conflict occurrence.

To solve (2), we rewrite the equation into the form

$$\frac{dy}{dt} - \phi y = -\phi y \left(\frac{y}{y_t} \right),$$

which is a Bernoulli equation.

Dividing by y^2 gives;

$$-y^{-2} \frac{dy}{dt} + \phi y^{-1} = \frac{\phi}{y_t}.$$

(3)

By letting $u(y) = y^{1-a}$ we convert the non-linear Bernoulli into 1st order linear system, and letting; $u = y^{1-a} = y^{-1}$ (since $a=2$ for the case above); then we;

$$u(t) = \frac{1}{y}, \quad (4)$$

$$\Rightarrow \frac{du}{dt} = -y^{-2} \frac{dy}{dt}.$$

Substituting (4) in (3), gives

$$\frac{du}{dt} + \phi u = \frac{\phi}{y_t}. \quad (5)$$

Equation (5) is the first order linear ODE. Since we have a varying parameter ϕ , we apply Laplace transformation to solve equation (5), which is rewritten as;

$$L\left[\frac{du}{dt} + \phi u\right] = L\left[\frac{\phi}{y_t}\right]. \quad (6)$$

The solution to (6) is given by;

$$u = \frac{\theta + (y_t - \theta)e^{-\phi t}}{y_t \theta}. \quad (7)$$

Since, $u(t) = \frac{1}{y}$, $\Rightarrow y(t) = \frac{1}{u}$, we can write the general solution equation (7) as;

$$y(t) = \frac{y_t \theta}{\theta + (y_t - \theta)e^{-\phi t}}. \quad (8)$$

where $y(0) = \theta$ is the initial conditions and y_t is the threshold condition for the occurrence of a conflict at time t .

To apply the dynamic model, consider a dependent variable Y_i defined by the indicator variable, that is;

$$Y_i = \begin{cases} 1 & \text{if there is environmental conflict} \\ 0 & \text{if there is peace} \end{cases} \quad (9)$$

Then a Bernoulli distribution fully describes this variable with parameter y_i ;

$$Y_i \sim \text{Bernoulli}(y(t)), \quad (10)$$

$$y(t) = \text{logit}(\phi) = \frac{y_t \theta}{\theta + (y_t - \theta)e^{-\phi t}}$$

Equation (10), gives the prediction probability model of conflict as a logistic function of a linear function of t . The value of ϕ which represents the state conditions and the estimation of the initial condition θ are important in modelling any situation using ordinary differential equation. In the context of environmental conflict, the initial conditions θ can be estimated as the state estimates of a conflict environment dependent on time whereas the state conditions ϕ which are not dependent on time but environmental

conditions are the observable characteristics at the particular instant.

2.0. Conflict environment dynamics

In general, if the desired state is specified for all the time, the requirements for the existence of a control variable (initial condition) that will generate the desired outcome $\phi(f)$, are very stringent. A less ambitious but more realistic goal is to require only a partial specification of the state variables. One such partial specification is forcing the state of a given system to attain a specified value at some finite time in the future. That is, given an initial time, t_0 an initial state $\phi(t_0) = x_0$, a final state $\phi(f)$, a control variable $\theta(t)$, and $t_0 \leq t \leq t+T$, for some finite time T , such that $\phi(t_0 + T) = \phi(f)$, there may or may not be a control variable, $\theta(t)$ which can force the system to attain the state $\phi(f)$. Thereafter it may be desirable to maintain the state $\phi(f)$ by a suitable choice of error coordinates of state variables.

A system is said to be completely state controllable if, for any initial state ϕ_0 , for any initial time t_0 , it is possible to generate an unconstrained control vector, $\theta(t)$ that will take any given initial state $\phi(t_0)$ to any final state $\phi(t_f)$ in a finite time interval $t_0 \leq t \leq t_f$.

In a conflict the control vector $\theta(t)$, determines the controllability of the state vector $\phi(t)$. Therefore, a completely output controllable system is specified as: if it is possible to generate a control vector $\theta(t)$ so that, for any t_0 , any initial systems output $y(t_0)$ can be transferred to any final output $y(t_f)$ in a finite time interval $t_0 \leq t \leq t_f$.

A companion concept of controllability in a conflict is observability. Observability implies the determinability of a state from an observation of the output over a finite time interval, starting from the instant at which the state is desired. A system is completely observable if, for some arbitrary initial state $\phi(0)$, there is a finite output such that from measurements of the output, ($y(0), y(1) \dots y(m)$), the initial state, $\phi(0)$ can be computed. In complex systems the observability of the system can be determined by examination of the coordinates of a transformation of the state vector $\phi(t)$. In some control problems, it is necessary to determine the state of the system in order to generate the appropriate control input (intervention). It is considered that observation of the output of a completely observable system, over a finite time interval, yields sufficient information to determine the state of the system at the beginning of the time interval. If the present time state is desirable, in general, only an estimate can be made and if a system is controllable then $\theta^*(t)$ an estimate of

$\theta(t)$ can be found. By selecting different trajectories (probable solution matrix) for the control variables over time a set of future 'histories' or behaviour can be built for the system. The problem is, however, to choose between the essentially infinite possible future histories, by no less than rigorous means. The most 'appropriate' history can be selected by choosing certain values of $\theta(t)$ through time.

3.0. Model for conflict prediction

In modelling a conflict, objective function, state condition and a set of initial conditions including possible additional constraints on values of variables and parameters through time or at initial/terminal time points are considered. In this paper, a model that uses the two components (state condition and a set of initial conditions) to model environmental conflicts is presented.

Suppose the general objective function that describes the general aspirations of the parties to a conflict is given by:

$$J(\phi(t), \theta(t), t) \quad (11)$$

Then the desired yield is achieved when the objective function J is optimized at a finite time horizon through $\theta^*(t)$ which is the estimate of $\theta(t)$ (initial conditions) in equation (12) such that

$$J = \int_0^t \lambda(\phi(t), \theta(t), t) dt \quad (12)$$

Suppose we have a state set, $\theta(t)$ represented by:

$$\theta(t) = \phi(t)_{i \in N} \theta_i, \quad (13)$$

where N is a set of parties to a conflict, $\phi(t)$ is the state vector, θ_i is the control vector of the system at i ; $i \in T$.

Then, a state is assigned a prior belief $P(\theta_i)$ which reflects existing knowledge about

$$\text{posterior} = p(\theta_i / D) = \frac{p(D / \theta_i) p(\theta_i)}{\int_N p(D / \theta_i) p(\theta_i) d\theta_i} = \frac{\text{likelihood} \times \text{prior}}{\text{normalizer}}. \quad (14)$$

where $\int_N p(D / \theta) p(\theta) d\theta$ is used to ensure that the values of $P(D / \theta)$ sum up to one and thus define a proper probability distribution. The new outcome $p(\theta_i / D)$ is therefore an estimate of $\theta(t)$.

Since the new outcomes estimated by equation (14) are from unconstrained control variables (which sometimes can be considered to be demands), there is every likelihood of going beyond the boundaries of the conflicts. It is therefore imperative to provide constraining mechanism to ensure that conflict demands and trajectories of the solution to equation (23) are guided. Omwenga et al (2010) presents a mechanism through which these demands can be managed. For instance, if in a conflict the first party has made demand y based on the current state variable set θ , then the second party will chose between the demand and its

the conflict and as the system evolves; some new information and data (say) D will become available, Omwenga et al (2010). These new outcomes which represent the available beliefs can be estimated and updated using the Baye's rule given by;

reservation value given by $R_2 + \ell_2$ (where R_i is the public information and ℓ_i is the private information). This presents equilibrium cut-point strategy for the second party given by:

$$s_2(y, \ell_2) = \begin{cases} \text{accept} & \text{if } y \geq R_2 + \ell_2 \\ \text{reject} & \text{if } y < R_2 + \ell_2 \end{cases} \quad (15)$$

Since ℓ_2 is private, the first party does not observe it and therefore observability concept in a conflict is not compromised, but must assess the probability that the second party will accept or reject his demand using the relation;

$$\begin{aligned} \Pr(\text{accept} / y) &= \Pr(y \geq R_2 + \ell_2) \\ &= \Pr(\ell_2 \leq y - R_2) \\ &= F_{\ell_2}(y - R_2). \end{aligned} \quad (16)$$

Considering the optimization problem for the first party, given the second party's strategy (16), then the expected utility for the first party is:

$$E_{U_1}(y / Q^*) = F_{\ell_2}(y - R_2) \cdot (Q^* - y) + (1 - F_{\ell_2}(y - R_2)) \cdot (R_1 + \ell_1), \quad (17)$$

where Q^* is the upper bound of the contested prize.

By the first order condition (F.O.C) and the log-concavity of f_{ℓ_2} , the first party's optimal demand is the unique y^* that implicitly solves,

$$y^* = Q^* - R_1 - \ell_1 - \frac{F_{\ell_2}(\cdot)}{f_{\ell_2}(\cdot)}. \tag{18}$$

However, $0 \leq y^* \leq Q^*$ and sometimes y^* will be outside the feasible set. We can then show that an end-point (0 or Q^*) is optimal and in any perfect Bayesian equilibrium (PBE), the first party will have the strategy:

$$s_1(\ell_1 / R_1, R_2, Q^*, F_{\ell_2}(\cdot)) = \begin{cases} Q^*, & \ell_1 \leq -R_1 - \frac{F_{\ell_2}(z)}{f_{\ell_2}(z)} \\ y^*, & -R_1 - \frac{F_{\ell_2}(z)}{f_{\ell_2}(z)} < \ell_1 < Q^* - R_1 - \frac{F_{\ell_2}(z - Q^*)}{f_{\ell_2}(z - Q^*)} \\ 0, & \ell_1 \geq Q^* - R_1 - \frac{F_{\ell_2}(z - Q^*)}{f_{\ell_2}(z - Q^*)} \end{cases} \tag{19}$$

where $z = Q^* - R_2$.

Taking variables $\delta_k, k \in \{0, y, 1\}$ such that $\delta_0 = 1$, if $y = 0$, $\delta_y = 1$, if $0 < y < Q^*$ and $\delta_1 = 1$, if $y = Q^*$, that is, a censored model with a ‘‘latent’’ best demand in the constraint set. Otherwise, there is the best feasible offer, at a boundary point.

$$L = \prod_{i=1}^n \Pr(y^* < 0)^{\delta_0} \cdot \Pr(y^* = y)^{\delta_y} \cdot (1 - \Pr(y^* < Q^*))^{\delta_1} \cdot \Pr(\text{accept})^{\delta_{\text{accept}}} \cdot \Pr(\text{reject})^{1 - \delta_{\text{accept}}} \tag{20}$$

where y^* = ultimatum demand from the first party to the conflict, Q^* = upper bound of the contested prize, δ_i = actions, $\sigma_i : \ell_i \rightarrow A^i, i = \{1, 2\}$, where A^i defines the action set for the i^{th} party.

Equation (20) is based on the existing control variables and it gives the log-likelihood function for the data in terms of distributions already derived, which are functions of regressors.

Using equation (20), the Likelihood, $P(D / \theta_i)$, which is a measure of the probability of seeing

Taking the second party’s acceptance as $\delta_{\text{accept}} = 1$, if it has accepted the demand and $\delta_{\text{accept}} = 0$ if it has rejected the demand and assuming we have data on both parties actions (i.e., y and δ_{accept}) from the current state variable set, θ the likelihood would be,

particular realization of the state θ , can be estimated as

$$\theta^* = \frac{Lp(\theta)}{\int_N p(D / \theta) p(\theta) d\theta} \tag{21}$$

According to Omwenga and Mwita (2010), a conflict with control variable ℓ_i , can be defined by a Baye’s probability distribution which is drawn independently and identically distributed (i.i.d) from a logistic distribution function $F_i(\cdot)$ with a corresponding everywhere positive density $f_i(\cdot)$, mean $\mu_i = 0$ variance $\sigma_i^2 < \infty$, assuming that f_i ’s are continuously

differentiable. Therefore, a state equation for a conflict environment is defined by the relationship;

$$\frac{dy}{dt} = \phi y \left(1 - \frac{y}{y_i} \right) \quad (22)$$

whose analytical solution is given in section 1.1, that is,

$$y(t) = \frac{y_i \theta(t)}{\theta(t) + (y_i - \theta(t)) e^{-\phi t}} \quad (23)$$

with the estimates of $\theta(t)$ given by (21), therefore the trend model for a conflict environment is given by:

$$y(t) = \frac{y_i \theta(t)^*}{\theta(t)^* + (y_i - \theta(t)^*) e^{-\phi t}} \quad (24)$$

$$\text{where } \theta(t)^* = \frac{Lp(\theta(t))}{\int_N P\left(\frac{D}{\theta(t)}\right) P(\theta(t)) d\theta(t)} \quad (25)$$

4.0. Application of the model in environmental conflicts

According to Libiszewski (1992), an environmental conflict is caused by the environmental scarcity of the resource that means: caused by a human-made disturbance of ecosystem's normal regeneration rate. Environmental conflicts are therefore the result of anthropogenic activities that strain and damage the environment. If the activities exceed environmental thresholds, y_i there is an increased probability of armed conflicts. Sprinz

(1998) describes environmental thresholds as the states in which the functioning of natural systems changes fundamentally. They can be estimated as ratios based on the current state and future capacities of the environment.

In applying the model it is assumed that the threshold, y_i and the state conditions $\phi(t)$ are known and generally have a marginal change on the overall model. They are therefore, assumed to be constants over time. Further, the application of the model to environmental conflict is depended on the condition that the conflict follows a Bernoulli distribution with parameter y_i defined by the indicator values given by:

$$X_{ic} = \begin{cases} 0 & \text{if } c \text{ is not in conflict in year } t \\ 1 & \text{if } c \text{ is in conflict in year } t \end{cases} \quad (26)$$

The application of the model to predict occurrence of a conflict starts by the estimation of initial conditions in a conflict situation. Modelling the initial conditions in this situation can be compared to the modelling of the risk related to the previous conflict Clementine, Dirk and Francois (2008). It is believed that environment that have experienced a conflict are more prone to another conflict in the future and thus their risk levels are high. This paper proposes a model that estimates the initial conditions which can act as the pointer to the current risk levels using the past and current state control variables. The estimates of the initial conditions can be used to make

predictions for the future trends of a conflict in a dynamic state system.

Now, assuming that regions under investigation for a conflict form a universal set Ψ and the regions that are likely to be in a conflict are its subset denoted by Q^* . The concern is on the subset which can be described as the “prize”. A region becomes an element (member) of Q^* if it has experienced a conflict at any time in the period of interest. The set Q^* is described as a semi-open space since it

$$m_t = \sum_{c=1}^n X_{tc} \quad \text{if } X_{tc} = 1 \text{ and } \exists y < t / X_{yc} = 1 \quad (28)$$

The number of regions that have experienced a conflict before time t , they are not at conflict in time t , but are reported to have experienced another conflict later is:

$$z_t = \sum_{c=1}^n X_{tc} + 1 \quad \text{if } X_{tc} = 0 \text{ and } \exists y < t, j > t / X_{yc} = 1, X_{jc} = 1 \quad (29)$$

The number of regions at conflict in time t that are reported to be still at conflict at any later period is:

$$r_t = \sum_{c=1}^n X_{tc} \quad \text{if } X_{tc} = 1 \text{ and } \exists y > t / X_{yc} = 1 \quad (30)$$

Therefore, the total number of conflicts in a region which is subset of Q^* is:

$$a_c = \sum_{c=1}^n X_c \quad (31)$$

The probability, $P(D/\theta)$ given by equation (14) that a conflict is likely to occur given that a region is a member of Q^* in time t can be estimated by:

$$P(D/\theta) \equiv L = \frac{m_t r_t}{m_t r_t + s_t z_t} \quad (32)$$

allows individuals to become members but does not allow them to get out.

Using the indicator variable X_{tc} , defined in equation 26, we have the following scenarios:

The total number of regions in a conflict in time t is:

$$s_t = \sum_{c=1}^n X_{tc} \quad (27)$$

The number of regions that are at conflict in time t and have experienced at least one armed conflict in the past is:

And the prior belief $P(\theta)$ which reflects on the existing knowledge about the conflict together with information on how the conflict evolve can be obtained as:

$$P(\theta) = \frac{a_c}{s_t} \quad (33)$$

Now, using the data set extracted from PRIO/Uppsala Conflict Data Project, obtained from <http://www.prio.no/cwp/ArmedConflict> and the estimated values by equation (32) and

(33), then the estimated initial condition $\hat{\theta}$, for the various conflict situations in the various regions in the year 2000, 2003 and 2004 are

obtained using equation (25) as given in table 1 below:

Table1: Estimated initial conditions as posterior

Country	2000		Country	2003		Country	2004	
	$\hat{\theta}$	No. of conflicts		$\hat{\theta}$	No. of conflicts		$\hat{\theta}$	No. of conflicts
India	0.68	8	India	0.69	7	India	0.74	6
Nepal	0.60	1	Nepal	0.60	1	Nepal	0.67	1
DRC	0.50	1	DRC	0.34	-	DRC	0.56	-
Colombia	0.68	1	Colombia	0.68	1	Colombia	0.74	1
Peru	0.14	0	Peru	0.14	0	Peru	0.18	0
Pakistan	0.49	1	Pakistan	0.49	1	Pakistan	0.56	2
Ethiopia	0.68	3	Ethiopia	0.69	2	Ethiopia	0.74	2
Turkey	0.68	1	Turkey	0.69	1	Turkey	0.74	1
Indonesia	0.55	1	Indonesia	0.55	1	Indonesia	0.52	1
Mali	0.25	0	Mali	0.25	0	Mali	0.31	0
Nigeria	0.14	0	Nigeria	0.14	0	Nigeria	0.18	1
Niger	0.37	0	Niger	0.25	0	Niger	0.31	0
Thailand	0.55	0	Thailand	0.55	1	Thailand	0.62	1

From table 1, $\hat{\theta}$ represents the estimated initial conditions for the various regions based on the past conflicts and the current state conditions. The estimates reflect the risk level of an occurrence of a conflict and it gives a pointer to the likelihood a conflict occurring given the past and present state conditions.

Using the estimate of $\hat{\theta}$, we can then build a prediction model for the various conflicts using equation (24). For instance, considering the case of India and using the year 2004 initial condition estimate of $\hat{\theta}$ obtained as

0.74, the future conflict predictor value assuming 2004 as the baseline, will be given by;

$$y(t) = \frac{0.74y_t}{0.74 + (y_t - 0.74)e^{-\theta t}} \quad (34)$$

We can then estimate y_t which represents the threshold for occurrence of a conflict at time t . This estimate follows a Bernoulli distribution given by

$$y_t = \hat{\theta}^x (1 - \hat{\theta})^{1-x} \text{ for } x = 0,1 \quad (35)$$

where $\hat{\theta}$ is the probability that a conflict will occur given the past and current state conditions. For the case of India in the year 2004 it is estimated to be 0.74.

The estimate of $\phi(t)$ can be computed using the relationship given in equation 13, i.e.

$$\phi(t) = \frac{\hat{\theta}}{\theta_i} \tag{36}$$

where θ_i is the control vector of the conflict system at level i which can be estimated as a prior condition by equation 33.

Using the value obtained from table 1, we can then obtain a likelihood predictor value for conflict occurrence by substituting the values for $\phi(t)$ and y_t into equation 34. From the data set in table 1, for the case of India, the values for $\phi(t)$ and likelihood predictor value are estimated as:

$$\phi(t) = \frac{\hat{\theta}}{\theta_i} = \frac{\hat{\theta}}{P(\theta_i)} = \frac{\hat{\theta}}{\frac{a_i}{s_i}} = \frac{\hat{\theta} s_i}{a_i} = \frac{0.74 * 9}{6} = 1.11$$

$$y(t) = \frac{0.74 \times y_t}{0.74 + (y_t - 0.74)e^{-1.11t}} \tag{37}$$

where t is the time period.

From 37 we can obtain an estimate of the conflict predictor value as a probability estimate.

Taking the case of India, we can estimate the value of y_t as follows:

$$y_t = \hat{\theta}^x (1 - \hat{\theta})^{1-x} = 0.74^1 (1 - 0.74)^{1-1} = 0.74$$

Substituting this value in equation 37, we get;

$$y(t) = \frac{0.74 \times 0.74}{0.74 + (0.74 - 0.74)e^{-1.11t}} = 0.74$$

The result gives a positive prediction of the occurrence of a conflict in a subsequent year considering the previous conflicts experienced by the region. However, since the threshold values, y_t are dependent on the interplaying variables within a conflict environment, it is anticipated that they will be variant and hence different value of $y(t)$ can be obtained for different values of y_t . Assuming different values of y_t for the case of India, table 2 gives the conflict prediction value given initial condition $\hat{\theta}$ value and state condition vector $\phi(t)$ for India using 2004 as the baseline year.

Table 1: Conflict predictor values at different thresholds

$\hat{\theta}$	y_t	$\phi(t)$	$y(t)$
0.74	0.2	-0.10436	1.052632
0.74	0.3	-0.10436	0.882353
0.74	0.4	-0.10436	0.816327
0.74	0.5	-0.10436	0.78125
0.74	0.6	-0.10436	0.759494
0.74	0.7	-0.10436	0.744681
0.74	0.8	-0.10436	0.733945
0.74	1	-0.10436	0.719424

Note: A zero or near zero threshold is generally not acceptable since environments or states are always in a state of conflict referred to as latent conflict.

With increase in the threshold value y_t for the occurrence of a conflict, it implies the costs of the conflict are transferable to the aggressor and this outweighs the benefits hence slowing down likelihood of a disturbance on the

environment. It is therefore expected that the predictor value will decrease since the conditions triggering such an occurrence will not be motivating enough. This is demonstrated on figure 1.

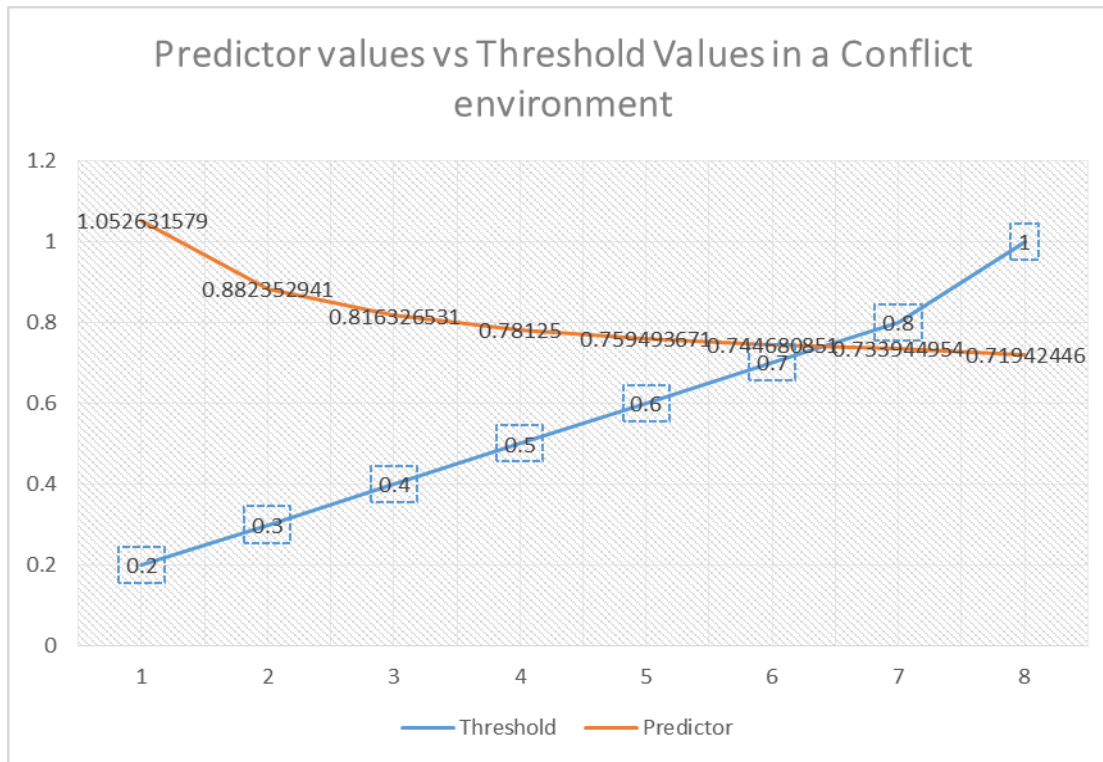


Figure:1: Predictor Values vs Threshold values in a conflict environment

From figure 1, an increase in threshold leads to a decrease in conflict predictor value and hence the likelihood of occurrence of a conflict. The prediction of a future occurrence of a conflict is thus dependent on the past and current state conditions which influences on the initial conditions $\hat{\theta}$, state condition vector $\phi(t)$ and the y_t .

5.0. Conclusion

In sections 3.0, we have provided a mechanism for the restrictions on the choices for the parties to the conflict and this has enabled us to express the outcomes as probability (weighted) of individual ideals. The restriction has the advantage of encapsulating most of the inherent optimality conditions in the Game theory. Through this approach we are able to estimate the likelihood of an occurrence of a conflict and make a prediction using dynamic models.

The model developed is a prediction model for the trend in the likely event of change in the threshold within a conflict environment and can be used to project on the anticipated outcomes in a conflict. In the context of determining environmentally-induced conflicts, environmental threshold values play a decisive role, since exceeding them is the sufficient condition for *environmentally-induced* armed conflicts to occur.

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