Chapter 6

A Study of

Chaotic Dynamics and Catastrophic Discontinuities

in

Bangladesh Trawl Shrimp Fishery

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6.1. Introduction:

Studies on the application of theory of chaos in the management of fishery prove that chaotic dynamics are more likely to happen when there is either, (i) the system is under open access, (ii) the high discount rate prevails or (iii) the demand curve is relatively inelastic. Actually, all these three factors ultimately lead to possible 'overexploitation' of the resource i.e. 'overfishing'/ 'overharvesting' of fishery. Clark (1973) thus said that "population can be driven to extinction by commercial hunting hardly needs to be emphasized".

Gordon's (1954) theory of common property fishery' and Hardin's (1968) tragedy of commons', both of which have since become classic, explained the logic behind the tragic consequence of exploitable natural resources under 'open-access' system. Marine fishing zone of Bangladesh in Bay of Bengal is not an "open access' in true sense. In fact, a very few resource stocks anywhere in the world at present satisfy the definition of open-access in true sense in general and fishery in particular. But, many theoretical studies of recent times and empirical verification on past data of either extinct or depleted fish stocks amply prove that the chances of this tragic consequence still persist. It may be for the reason of biological overfishing in spite of the fact that the system is not purely 'open access'.

So far the social discount rate is concerned, the marine resources of the area under study being exploited by the common fisher folk of a less developed country, the rate may expectedly be very high. Besides, we have found that the shrimp fish price is sticky, though the demand curve is not perfectly elastic (Figure 3.2, 3.4 and 3.6). Analysis of the results of our study in the last two chapters amply prove that, though the system officially is not under 'open access', overfishing is causing reduction in both the biomass stock and harvest with increasing effort level over the last few years.

In this context, it may be recalled that Lisbon Principles (Portugal, 1997) were laid down to address five major problems in the oceans. These are overfishing, ocean disposals and spills, the destruction of coastal eco-systems, land-based contamination and climate change. Of 200 major fish stocks accounting for 77% of world marine landings, 35% are currently classified as overfished (Costanza *et al,* 1998). Overfishing is, therefore, identified as the most serious problem of these five as the complex dynamics arising from non-linearities in fishery can show chaotic and catastrophic dynamic patterns (Rosser, 2001). Though overfishing has multiple causes and varies fishery to fishery, study of non-linear complex dynamics of a species which is targeted for large scale commercial exploitation has invited a lot of attention from researchers who have been trying to understand 'chaos' in fishery.

6.1.1. Chaos and Catastrophe:

The term 'chaos' often appears to be misleading and confusing. It is precisely defined as *'effectively unpredictable long-time behaviour arising in* a *deterministic dynamical system because of sensitivity to initial conditions'.* Thus, given the perfect knowledge of the initial conditions, a deterministic system is perfectly predictable and, in practice, is always predictable within short time span. However, any observed time series from chaotic systems may appear irregular and disorderly as a consequence of long-term unpredictability. It implies that chaos is definitely not to be confused with complete disorder. It is in-fact a disorder but in such a dynamical system which is deterministic and always predictable in short run. Thus chaos theory as a scientific theory about situations that obey particular laws but appear to have little or no order, identifies that i) any complex system has an underlying order and ii) any apparently simple system can produce complex behaviour.

On the other hand, catastrophe connotes such a sudden event that causes destruction or unfavourable/undesireable eventuality what may usually be termed as a calamity. Complex dynamics arising from non-linearities can show chaotic and catastrophic dynamic patterns (Rosser, 2001). While chaotic systems tend to remain bounded and thus may represent sustainable solutions despite associated apparently erratic nature of the dynamics, catastrophic discontinuities demands special investigation to determine the critical boundaries within which the system must be kept in order to maintain sustainability.

Experts are unanimous that management of fisheries operates in a highly uncertain environment. Harvest levels of most of the fisheries worldwide in recent years record large fluctuations. This is also reported in estimated stock levels. Since fish stocks cannot be observed directly, estimates of present and past stock levels are themselves subject to considerable error. Conard, Lopez and Bjorndal (1998) show that observational errors can combine with biological stochastic to generate a non-linear increase in risk. Zimmer (1999) shows that environmental noise can interact with endogenous chaotic population dynamics to generate fluctuations of greater variance. It must be recognized that on top of the noise from environment there is the problem of noise induced by the poor information available to fishery managers and policy makers regarding the actual state of *any* fish population.(Rosser, 2001).

The chaotic behaviour in fisheries is required to be studied from the angle of population dynamics of the fish as well as the economic characteristics of the harvesting process. Instability' in simple bioeconomic model due *to* harvest activity has already been reported (Hilborn and Walters,1992; Opsomer and Conard, 1994). On the other hand, relatively low cost of harvesting with respect to price may cause backward bending supply *curve.* This is an economic phenomenon which creates the condition of multiple equilibria some of which may be 'bad' and unstable. Moreover, fishery dynamics subject to stochastic constraints of ecologic and economic are in most cases nonlinear. So multi-disciplinary modeling of fishery dynamics should be such that must be nonlinear and complex but be able to capture its irregular or chaotic behaviour. It should be such that the economic agents would be able to successfully follow an underlying truly chaotic dynamics, even through a self-fulfilling chaotic mistake, (discussed in 6.3) so that system does not lead to the collapse of that fishery. In this chapter, we have attempted to study the possibility of existence of backward bending supply curve as well as consequential chaotic dynamics and catastrophic discontinuities in large scale commercially exploited trawl shrimp fishery in Bay of Bengal (Bangladesh). Our objectives of study in this chapter are to find the following:

(i) whether the supply *curve* of marine shrimp fishing of Bangladesh shows any sign of backward bending at any level of discount rate.

(ii) Whether any tangent bifurcation of such bending supply curve with the demand curve exists and at what rate of discount.

(iii) Whether catastrophic discontinuities exist as a possibility or the system is deterministically chaotic.

6.2. A Brief Discussion on Chaos and Catastrophe in Fishery Management:

May (1974) first introduced the term 'chaos' into the study of dynamical systems in ecological populations. He focused deterministic chaos in biological growth processes on the growth sector of bioeconomic models. Hassell et al. (1976), however, found that the intrinsic growth 'energy' required for a chaotic stock growth process is significantly greater than the actual intrinsic growth of fish stocks world-wide. Thus, it appears that fish stock growth relations themselves cannot generate deterministic chaotic fluctuations. Hence, the ecological deterministic chaos will not be an endogenous component of a bioeconomic fisheries model unless the model is extended to include a more comprehensive 'chunk', of the ecological system to be studied. Although, Zimmer's (1999) study of chaotic dynamic systems in natural populations does not corroborate this fully. However, similar controversy exists in economics with some arguing that *certain* markets, especially in agriculture, exhibit chaotic *dynamics* (Chavas & Holt, 1991,1993 ; Finkenstadt and Kuhbier, 1992), whereas others question such findings and argue that true chaotic dynamics have not been definitively established for any economic time series (Jaditz and Sayers, 1993 ; LeBaron, 1994). Chen (1997) argues that the combined interaction of the global climate and economic systems may be a chaotically dynamic system.

Similarly, the chaotic behavior in fisheries are not likely to originate simply from the population dynamics of the fish stock but also from the economic characteristics of the harvesting process. It is also to be noted that harvest activity can produce instability in simple discrete-time bioeconomic models (Hilborn and Walters, 1992; Opsomer and Conard, 1994). In these models, harvest adjustments depend on previous profit with exogenously determined multiplicative adjustment of sensitivity parameters. Actual stability depends on the interplay of population dynamics and market conditions. Harvests can have an unassuming destabilizing effect under certain growth and market conditions. Market oriented harvest may also have a stabilizing influence, even when applied to stocks having extreme intrinsic growth rate. Conklin and Kolberg (1994) address the question of whether market-driven harvest activity has a stabilizing or destabilizing influence on stock fluctuations. They observed that 'chaos may be lurking in unexpected place in renewable resource models when harvest is market-driven'. They verify their predictions in the context of the Pacific Halibut fishery. Their model has beenfound to be capable of exhibiting chaotic behavior under a range of plausible market conditions. However, they had to make the note that Pacific Halibut Fishery was not necessarily on the verge of behaving chaotically even though their model exhibited many of the features of chaos.

Harvest activity can influence the dynamic model by two ways - one through the 'growth factor' and other through the 'market response effect'. The growth factor has a systematic influence on stability of the bioeconomic equilibrium point along a given open-access supply iocus. The 'market response effect' involves variation in harvest in response to the stock level changes. Conklin and Kolberg (1994) found that changing slope of the demand curve could thrust the model into instability, chaos and extinction without changing.the bioeconomic equilibrium point. They also showed that the increased market demand without changing the slope of the demand curve i.e. enhanced market response due to expansion of the market, could push the model into instability, chaos and even extinction.

While it is relatively simple to understand mathematically that deterministic chaos is potentially important in fisheries, it has yet to be established how far the fluctuations in real-world system outputs {biomass stock, harvest, etc.) are due to chaos rather than to stochastic influences. The assertion by Wilson *et ai.* (1994) that the fisheries may be 'chaotic' has been challenged by Fogarty (1995) on the ground that very few available proper documentation of chaos in ecological systems may hardly be considered sufficient to conclude affirmatively.

However, for analysis and management of chaotic fishery dynamics, the long-term forecasting of system outputs have generally been regarded as doubtful due to critical dependence on initial conditions. The accuracy of short-term forecasting, on the other hand, depend on the type of forecasting model used. McGIade (1994) points out that the predictive power of short-term forecasting will be poor when chaotic time series are modeled using a linear stochastic process. However, while the long-term unpredictability *of* chaotic fisheries systems may certainly complicate the task of resource managers, it does not negate the management function completely. Fogarty (1995) argues that the issues of predictability and control are different. Grafton and Silva-Echenique (1997) show that the uncertainty caused by chaos does not necessarily imply a 'precautionary' approach to the fisheries management but rather a 'mixed strategy' approach. This approach provides managers more options for controlling fisheries even when the dynamics of the system are not known. Now, apart from this theory of chaos', other theories that have been developed in the field of studying dynamic behaviour, particularly in the field of dynamic discontinuities, is the catastrophe theory. The catastrophe theory developed by Thorn (1975) and Zeeman (1977) may be regarded as the best expressed mathematical approach to modelling dynamic discontinuities. The collapse of the blue whale population (Jone and Walters, 1976) was studied by the application of catastrophe theory.

6.2.1. Fishery Dynamics and Economics:

The explanation of collapse or sudden biomass shift of fishery was initiated from the economic point of view by the revelation of the possible existence of backward bending supply curve - under certain conditions.

Copes (1970) first described the backward-bending open-access supply curve in fisheries subject to the condition that average revenue equals average cost of effort. He contrasts this case to the optimal supply curve (for 8=0) in which marginal revenue equals marginal cost of effort. He identified the open-access that had long been understood as a prime source of aggravating the overharvesting problem in many fisheries (Gordon, 1954; Hardin, 1968). However, Clark (1990) shows that such a backward-bending outcome even can occur in an optimally managed fishery without open access, as long as there is sufficiently high discount rate. In such cases we already know that chaotic dynamics can arise in fairly simple models with discrete dynamics. Conklin and Kolberg (1994) have provided a specific model of chaotic dynamics for the Pacific Halibut fishery with'such a backward-bending supply curve. In economics of fishery, such backward-bending supply curve is assumed to be derived from such optimally managed fish resources by a sole-owner whose objective is to maximize discounted revenues.

As the objective is assumed to be maximization of discounted revenues, then two aspects become very important: First one is the price of the resource as revenue directly depends on price. It has also been known (Clark, 1973) that extinction is always feasible if extinction cost is less than the price. It is important to note that as the owner maximizes discounted future revenues, the price actually implies future price. Second important aspect, therefore, is the expectation regarding the future price as the owner decides his harvesting policy prior to realization of actual price in the market. The expectation of realizable price is every time formed out of the realized price at present. Because of the fluctuations in observed prices, formation of expectation is an adaptive learning process. Hommes and Rosser (2001) studied the price fluctuations under adaptive learning in renewable resource markets such as fisheries.

Most of the economic models thus involve a description of human behaviour with a basic postulation that economic agent behaves rationally. This postulation of 'rational behaviour' has two different aspects. One of the aspects is that economic agents always behave optimally in any given situation. Thus economic agent is always either a utility/profit maximizer (or cost minimizer). The second aspect of rationality is that 'agents form expectation about the future in a way that is not systematically wrong'. There is no disagreement among the economists regarding the way optimization behaviour of the first aspect be formulated. But there are various options on how one should, model the second aspect of rationality. Because of this possible difference in the second aspect, the conditions under the adaptive learning process vary. Economic agents form an expectation regarding price in future which decides upon certain decisions like harvesting at present and again, the actual realization of price at present decides upon his expectation formation of the future price. The difference between the expected price and actual realization of price is mistake which the *economic* agents want to minimize systematically. *Economic* agents thus want to be within the predicted limit of mistake. If the actual realization of price appears outside the calculated limit frequency, then the economic agent is said to be irrational due to his systematically wrong expectation formation. A dynamic economic model, for this reason, is considered always an expectation feedback system - expectation affect actual dynamics and actual dynamics feedback into the expectation scheme. This is what we called Rational

Expectation Hypothesis (REH) - the most predominant paradigm in expectation formation in economics, which was first introduced by Muth (1961) and was first applied to macroeconomics by Lucas (1971). The REH describes an equilibrium point which is a fixed point of this expectations feedback system and is known a rational expectation equilibrium (REE). Though REE is very much appealing as a normative model of expectation formation, it requires that the information set on market forces is completely known to the economic agent in such a way so that agent can compute the equilibrium point instantaneously and takes his decision accordingly. This is an extreme task, if not impossible task, imposed on economic agent. Under non-linear market equilibrium condition, even if all the market equilibrium conditions are known to the economic agent at every point and in every time, in most of the cases it would be impossible to find the equilibrium point analytically and would require the computing power like super computer to find the equilibrium point numerically. Because of this practical impossibility, several alternatives have been proposed by many economists, like Bray (1982), Bray and Savin (1986), Marcet and Sargent (1989), Woodford (1990), Bullard (1994), Evans and Honkapohja (1995). Fundamental difference of expectation formation hypothesis of all these works with that of REH is that the economic agent does not require to have a complete information set on market forces but beliefs only on actual time series. Under this assumption, REE is not an obvious outcome of adaptive learning process within the expectations feedback system even asymptotically.

Hommes and Sorger (1998) introduced the notion of **consistent expectation equilibrium** (GEE) in non-linear dynamic economic models. The key feature of CEE is that "agents expectations of a certain variable are consistent with the realizations of that variable in the sense that their sample average and their sample autocorrelations are the same". For example, suppose that the agents believe that prices follow a stochastic low-order AR(k) process and thus predict that tomorrow's price will be some linear combination of past prices. Given this belief, a certain time path of actual prices will be realized through market clearing. In literature, this time path of equilibrium prices is called a CEE if its sample average and its sample autocorrelation function equal the average and the autocorrelation function, of the AR(k) belief process respectively. Stated differently, a CEE is a fixed point of the expectations feedback system in terms of the observable sample average and sample autocorrelations. CEE is thus "an equilibrium concept for which beliefs are self-fulfilling in a linear statistical sense" (Hommes and Sorger, 1998: 288). This approach is described as bounded rationality hypothesis in 'expectation formation and learning' where the agents base their expectations upon time-series observations and adopt their beliefs accordingly. This concept of consistent expectations equilibrium is crystallized as a more general framework by combining the notion of a **self-fulfilling mistake** (Grandmont, 1998) with constructions of Sorger (1998) and Hommes (1998). The concept of quasi-rational expectations introduced by Nerlove ef *al* (1979) may be compared with this approach. According to this approach, expectations about variable(s) are given by those predictor(s) that minimize the mean squared prediction errors in an ARIMA model. List of recent related works on bounded rationality and expectation formation includes the rational belief equilibria of Kurz (1994), the pseudo rational learning of Marcet and Nicolini (1995), the expectational- stability and adaptive learning rules of Evans and Honkapohja (1994, 1995), the perfect predictors of Bohm and Wenzelburger (1996), and the adaptive rational equilibrium dynamics of Brock and Hommes (1997; 1997a). Stability and instability of adaptive learning processes have been investigated by Grandmont and Laroque (1991), Bullard (1994), Grandmont (1998), Chatterji and Chattopadhyay (1996), and Schonhofer(1996).

6.3. Chaotic Dynamics and Catastrophic Discontinuities in Bangladesh Trawl Shrimp Fishery:

We use an optimal control theoretic version of the Clark-Gordon-Schaefer fishery model as proposed by Hommes and Rosser (2001). According to this proposition, the presentation of the optimal equilibrium supply and demand is in terms of a continuous model, whereas the price fluctuations in the corresponding speculative Cobweb dynamics are in discrete time. Characteristics of population or stock of shrimp, harvest h and growth function are identical to the description we have already made in earlier chapters. The intrinsic growth rate of the shrimp population (r), the ecological carrying capacity for the shrimp fishery (K) follow the same definition as in chapter-3 and assume the respected values estimated there. Catchability co-efficient (q) follows Gordon (1954) and reflects the level of technology used, labour employed and amount of capital invested. We accept the capital stock behaviour of Clark's (1990) dynamic models *m* which capital stock has inertia. Thus, the optimum levels of effort, stock and harvests at the infinite discount rate are identical to usual open-access equilibrium or bionomic equilibrium. The cost function is assumed as given in section 3.3.2. The carrying capacity K, the catchability co-efficient q, the marginal cost of effort c_2 and the intrinsic growth rate r being given, the optimal stock expressed explicitly by the equation 4.11 becomes a function of discount rate (6) and price (p). The equation 4.11 then can be written as,

4 pqK r pqK r pqKr

The optimal solution x^*_s is usually referred to as the bioeconomic equilibrium.

At this optimal population level, the corresponding optimal sustained yield is

$$S_6(p) = h = f[x;(p)] \qquad (6.2)$$

where, S_5 (p) is denoted as the discounted equilibrium supply curve.

As the discount rate 5 tends to infinity, then this discounted supply curve reduces to Gordon's (1954) open-access supply curve as shown below:

$$S_8(p) = \wedge(l - \wedge -) \qquad (6.3)$$

pq pqK

The equation (6.3) shows that for the price p> $\frac{Q}{qK}$^-, the discounted supply S_B (p)>0. Thus,

the price p = $\frac{-\hat{}-}{qK}$ is the minimum below which we assume that the equilibrium supply equals

zero.

In Bangladesh trawl shrimp fishery, the values of the parameters are given as (chapter-3), K = 11,400, q = 0.0000977332, r = 1.330818 and c_2 = 1156.76.
Substituting these Values in 6.1, we find the discounted equilibrium supply curve at different discount rate 8 . These discounted equilibrium supply curves are presented in figure 6.1. It is revealed that, at discount rate 5=0, that is, when far-distant future is considered as equally valuable to to-day, the supply curve of Bangladesh trawl shrimp fishery is upward sloping and approaches the maximum sustainable yield (MSY). But for 5 >0, the supply curve (6.2) appears as backward bending. We observe that the bionomic equilibrium x*(p) is a decreasing function of the fish price p and the population growth map is non-monotonic. Figure 6.1 shows that, as the discount rate 8 increases, the supply curve becomes more backward bending. Thus, the most backwardly bent supply curve must corresponds to the discount rate 5 = » , which usually means the myopic case. This is what corresponds to the open-access bionomic equilibrium case studied by Gordon (1954) and this is associated with overfishing situation. It is to be noted that the supply curve bends backward at such small values of the discount rate that makes sense with respect to economic explanation, in contrast to the rates that are necessary to generate chaotic dynamics in golden rule neoclassical growth models (Muntrocehio and Sorger (1996), Nishimura and Yano (1996), Mitra (1998).

As we know the fact that a backward-bending supply curve together with a sufficiently inelastic demand curve may lead to multiple steady state equilibria even for a static case, we like to investigate the parameters of the demand curve for which this phenomena is possible in Bangladesh trawl shrimp fishery. For this, we choose a simple demand function in linear form as

$$D(p) = A - B\,p \qquad (6.4)$$

The marginal demand B has been chosen intentionally so small to make multiple equilibria possible. Thus the value of marginal demand B = 0.00053. The constant A has been chosen such that at the minimum price, consumer demand would be exactly equal to the MSY. Hence, the value of A is given by,

$$A = \frac{Kr}{4} + \frac{Bc_2}{qK} \qquad (6.5)$$

and we obtain the numerical value of A=3793.35

This way of parameterizing the demand curve is adopted by researchers for convenience (Hommes and Rosser, 2001: 287). This is convenient to define well the price dynamics under adaptive learning and to remain bounded for all time. Linear demand curve with the given value of the parameters A and B thus plotted in figure 6.1 to investigate the existence of multiple equilibria. There are two extreme cases, when 5 = 0 and when 8 = ». Figure 6.1 shows that, at 5 = 0, there is a unique steady state equilibrium point. This point is (20,000, 3782.78). But at other extreme case at S = », because of backward bending, there would be three different steady state equilibrium points. In between these two extreme cases, naturally there would be a situation where a tangent bifurcation would create two equilibrium steady state points. We find that this 'two-steady-states' situation is created through a tangent bifurcation at 8=8*=0.12. In Bangladesh trawl shrimp fishery, therefore, at discount rate 8 greater than 0.12, there are three different equilibrium points. For example, in Figure 6.1, we indicate such three equilibrium points by mi, m_2 and m_3 for the discount rate 8=0.15>5*.

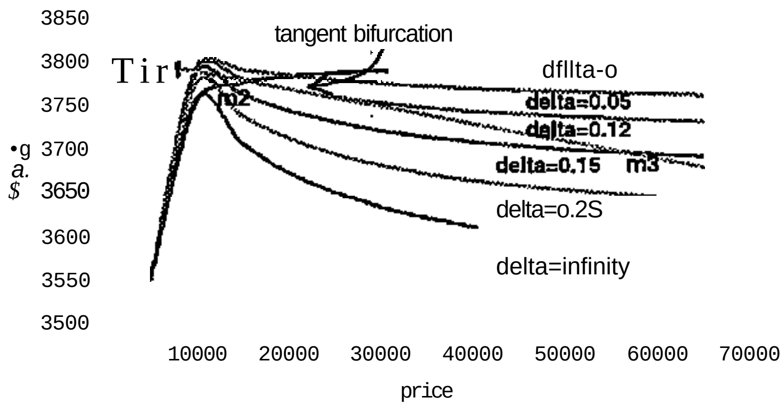

Figure 6.1: Demand and Discounted Equilibrium Supply Curves Ss in 6.2 under naive expectations for Different Discount Rates.

This finding verifies the original argument of Copes (1970) that in the case of strongly backward-bending supply curve, multiple equilibria are possible. But under this condition, increasing demand could lead to a collapse of a fishery and a jump in the equilibrium. This is what is called catastrophic discontinuities. The collapse of the Antarctic fin whales was tried to explain by the application of such catastrophe theory. The possibility of existing such a situation in Bangladesh trawl shrimp fishery exists provided discount factor 8>0.12 and the slope of the demand curve B = 0.00053. In the next section, we would try to investigate price dynamics under adaptive learning.

6.3.1. Price Dynamics of Bangladesh Trawl Shrimp under Adaptive Learning:

In the previous section, we have shown the equilibrium supply of Bangladesh marine shrimp when it is managed optimally. We can now consider price fluctuations under adaptive learning process. It has been shown theoretically by Hommes and Rosser (2001) that, in some fisheries, the naive forecasts can be improved in a linear, statistical sense, even when price fluctuations are chaotic.

Our objective is to investigate whether, under naive expectations, price fluctuations can be described by Cobweb type price dynamics and naive forecasts can be improved in the same way in case of Bangladesh trawl shrimp fishery. Following this, we will try to investigate CEE, as introduced by Hommes and Sorger (1998), in our proposed optimal control marine shrimp fishery model'of Bangladesh.

Cobweb Dynamics under Naive Expectations in Trawl Shrimp of Bangladesh: *in* order to study the price fluctuations in this marine shrimp fishery, we assume the following:

(i)Decision regarding investment for fishing equipment has been made by. the producers some fixed time period ahead of harvesting.

(ii)The optimal production decision is derived from the discounted equilibrium supply curve (6.2) when producers' price expectation is given.

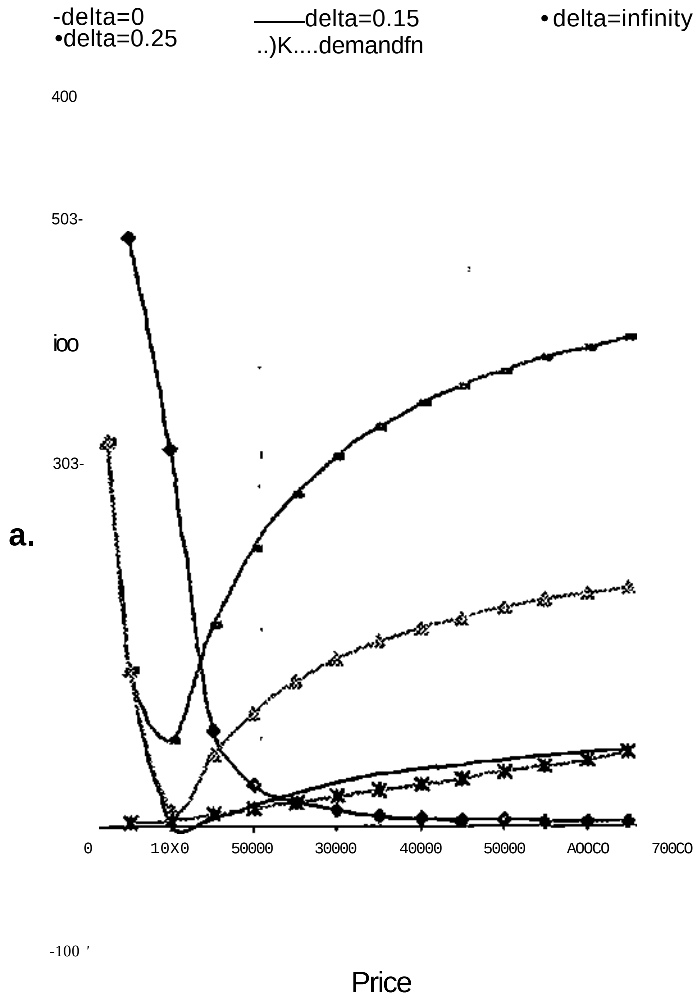

Figure 6.2: Implied Law of Motion under Naive Expectation Gs in 6.6 under naive expectations for Different Discount Rates.

(iii)Investment lag is one fixed time period, ahead of which price expectations are formed.

(iv)Adjustment period of fish stocks is one year (production lag).

Given the consumer demand function (6.4) and the discounted supply curve (6.2), the market equilibrium price at time 't' is determined by demand and supply. Thus we get,

$$D(p,) = S_s(P,^e)$$

Under naive expectations hypothesis, producers believe that expected current price will be last year's price and thus $P_t^e = P_{t-1}$.

Hence, the implied actual law of motion becomes,

$$P, = G_8 (p_{..,}) = D^{"J} S_s (p_{..,}) = \frac{A \sim S \wedge (p' - i)}{B} \quad (6.6)$$

Graphs of the implied actual law of motion G_5 under naive price expectation, for different values of the discount rate, are shown in Figure 6.2.

It is to be noted that we observe a critical parameter value S*=0.12 for Bangladesh trawl shrimp fishery. This is the critical value of the discount rate 8 for which tangent bifurcation occurs. At this point, number of steady states changes from one to two steady states. Thus for 8 < 0.12, there is only one steady state and for 8 >0.12, there are three steady states. But at bifurcation value, there are two steady states. Hence, for discount rate 0< 8< 8*, the unique steady state p_t = p*, for all 't', is the only rational expectation equilibrium (REE). But for discount rates 8 > 8*. as three steady states co-exist, there are multiple stationary REE.

To know whether economic agents, who are boundedly rational and do not have exact knowledge about underlying market equilibrium equations, would be able to discover regularities in their forecasting errors under naive expectations and change expectations accordingly, we find chaotic price series under naive expectations and corresponding chaotic forecasting errors for different values of discount rates (8 = 0.02, 8 = 0.10, 8 = 0.15), and are shown in Figure 6.3 to 6.8. Sample autocorrelations and partial autocorrelations of forecasting errors under naive expectations are presented in Table 6.1 to 6.3 for three different discount rates, two of which are less than 8* and other one is greater than 8*. Tables show that, for each of the discount rate, the chaotic forecasting errors have a strongly significant first-order autocorrelation co-efficient p > 0.4. Thus, it can be said that any boundedly rational agent would be able to conclude by using standard linear statistical tools that naive expectations are 'systematically wrong', even when prices fluctuate chaotically. It is, therefore, expected that economic agent in Bangladesh trawl shrimp fishery may try to improve effectively his/her forecasting accuracy and thereby, try to optimize the forecasting parameters by adaptive learning as additional observations become available.

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0 it
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Figure 6.3: Chaotic Prices Under Naive Expectations for 5=0.02

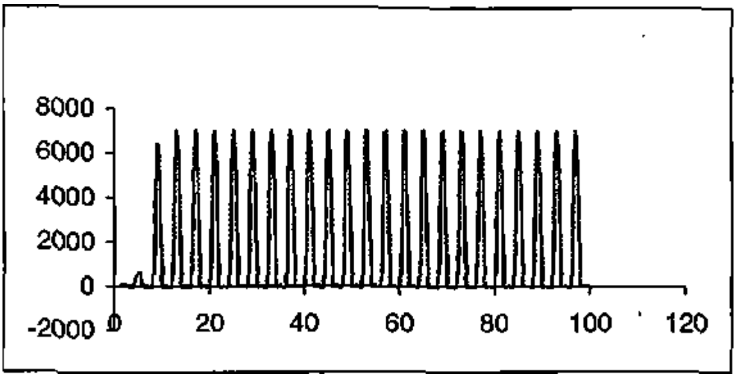

Figure 6.4: Chaotic Prices Under Naive Expectations for 5=0.10

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2000-
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* - c o i n c \ i a > (D » o | v . ^ j - , - c o i r > (N C »

Figure 6.5: Chaotic Prices Under Naive Expectations for 5=0.15

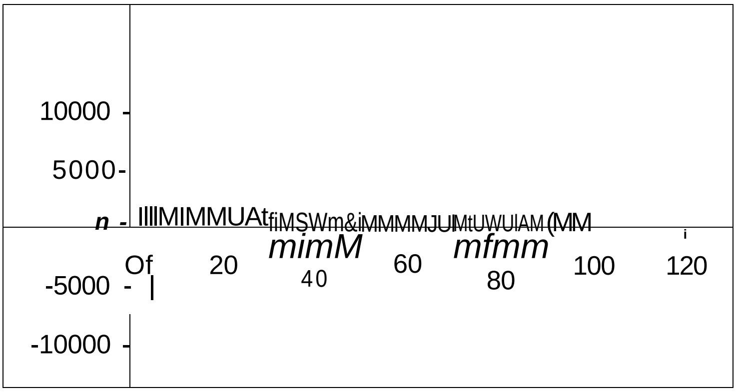

Figure 6.6: Chaotic Forecasting Errors Corresponding to Figure-6.3 Under Naive Expectations for 5=0.02

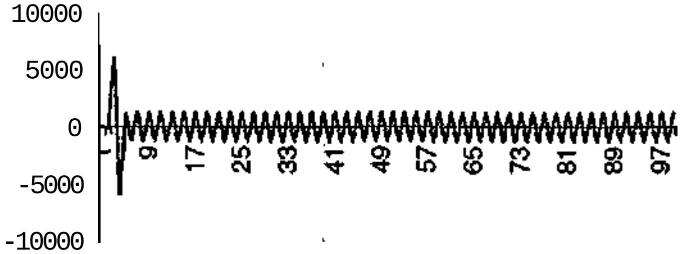

Figure 6.7: Chaotic Forecasting Errors Corresponding to Figure-6.4 Under Naive Expectations for 5=0.10

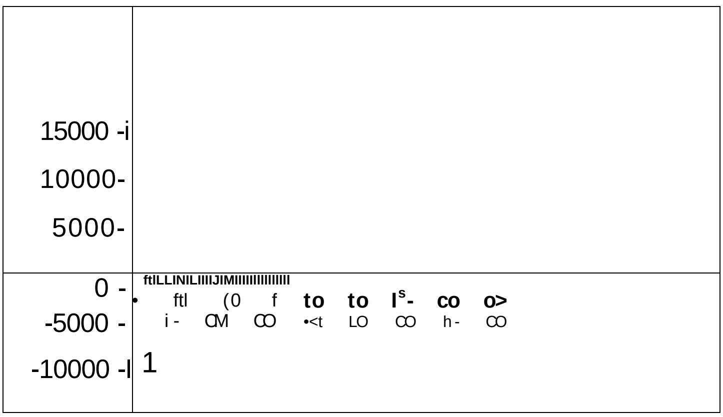

Figure 6.8: Chaotic Forecasting Errors Corresponding to Figure-6.5 Under Naive Expectations for 6=0.15

Table 6.1
Autocorrelations, Partial Autocorrelations and Box-Lung-statistics
of Forecasting Error under Naive Expectations for 5=0.02

Lag .	AC	PC	Box-Lunge-Stat.	Prob.
1	-0.861	-0.861	75.761	0.000
2	0.722	-0.076	129.415	0.000
3	-0.717	-0.441	182.941	0.000
4	0.712	-0.028	236.353	0.000
5	-0.705	-0.267	289.176	0.000
6	0.697	-0.014	341.406	0.000
7	-0.690	-0.178	393.151	0.000
8	0.683	-0.009	444.409	• 0.000
9	-0.676	-0.122	495.170	0.000
10	0.669	-0.007	'545.429	0.000

Table 6. 2
Autocorrelations, Partial Autocorrelations and Box-Lung-statistics
of Forecasting Error under Naive Expectations at for 6=0.10

Lag'	AC	PC	Box-Lunge-Stat.	Prob.
1	-0.499	-0.449	25.433	0.000
2	-0.001	-0.334	25.433	0.000
3	-0.481	-0.972	•49.491	*0.000*
4	0.963	-0.001	147.050	0.000
5	-0.481	-0.003	171.636	. 0.000
6	-0.001	-0.004	171.637	0.000
7	-0.459	0.100	194.510	*0.000*
8	0.919	-0.007	•287.352	0.000
9 .	-0.459	-0.006	310.765	0.000
10	-0.001	-0.004	310.766	0.000

Table 6.3
Autocorrelations, Partial Autocorrelations and Box-Lung-statistics
of Forecasting Error under Naive Expectations for 8=0.15

Lag	AC	PC	Box,-Lunge-Stat.	Prob.
1	-0.493	-0.493	24.597	*0.000*
2	0.000	-0.322	, 24.597	0.000
3	-0.004	-0.241	24.599	0.000
4	-0.001	-0.192	24.599	0.000
5	0.000	-0.159	24.599	*0.000*
6	0.000	-0.136	24.599	0.000
7	0.000	-0.118	, 24.599	0.001
8	0.000	-0.104	24.599	0.002
9	0.000	-0.092	24.599	0.003
10	0.000	-0.083	24.599	• 0.006

6.3.2. Consistent Expectation Equilibrium :

Hommes and Sorger (1998) defines CEE as under:

A triple {(p_t)^1_0; a, B), where (pj^o *s a sequence of prices and a and B are real numbers, pe [-1,1], is called a consistent expectations equilibrium if

(i) the sequence (p_t)™$_0$ satisfies the implied actual law of motion (6.10);

(ii) the sample average price p exists and is equal to a; and

(iii) the sample autocorrelation co-efficients pj, J21, exists and the following is true:

(a) if (P_t)^o is a convergent sequence, then sgn (pj) = sgn (B^1), j >: 1;

(b) if (p_t)^1_0 is not convergent, then pj = p', j > 1.

A CEE is a price sequence together with an AR(1) belief process such that the expectations are self-fulfilling in terms of the observable sample average and sample autocorrelations. Along a CEE, expectations are thus correct in a linear statistical sense and, using time-series observations only agents would have no reason to deviate from their belief.

Given an AR(1) belief, there are at least three possible types of CEE: (i) a steady state CEE in which the price sequence (pt)~$_0$ converges to a steady state price p*; (ii) a two-cycle CEE in which the price sequence (p_t)JI$_0$ converges to a period two cycle {p^Pj} with p* ^Pj; and (iii) a chaotic CEE in which the price sequence (p_t)™$_{=0}$ is chaotic.

If the economic agent is not naive and has a definite AR(1) belief process described by the parameters, say, a and p, then those parameters may be obtained as under:

Agents are normally supposed to stick to their belief over the entire time horizon. Moreover, it is necessary that the entire price sequence is to be known in order to verify the consistency of the implied actual dynamics. However, if we consider the adaptive learning situation as a slightly flexible one and assume, that agents change their forecasting function over time within the class of AR(1) beliefs and update their belief parameters ott and p_{ti} as additional observations become available, then a natural learning scheme that fits the framework of CEE is based upon sample average and sample autocorrelation.

Let us assume that economic agents do not know market equilibrium equations and form expectations based on time series data. Agents know all past prices {p_0, pt, ..., pt) and use these prices in their forecasting (P_t^e). They assume that prices are generated by a stochastic AR (1) process and follow a simple linear stochastic process. Let us assume thai expectations are homogeneous. Thus the expected price is given by

$$(P^c_{t+1}) = a,_+ p_l(p_t - o_t) \qquad (6.7)$$

where, at is the unconditional mean of the AR (1) process and p_t is the first order autocorrelation co-efficient.

For any finite set of observations {p_0, pi,..., pt) the sample average is given by

t + l$_{i=n}$

and the 1st order sample autocorrelation co-efficient is given by

i-\

$$0,=\wedge—,————•——————t>1. \qquad (6.9)$$

(=0

Thus p_t is a real number and B, E [-1,1].

When in each period the belief parameters are updated according to their sample average and their 1st order sample autocorrelation, the law of motion becomes,

$$Pi_{+}i = G_{Ui|li}(pJ = G(ii_t + p_1(p_t - a_t)), \qquad t > 0 \qquad (6.10)'$$

This dynamical system (6.8) to (6.10) is known as the *actual dynamics with sample auto-correlation learning* (SAC learning). The initial state for the system can be any triple (p_{0l} cio, Po) with poe [-1,1].

Theoretically, three typical observed outcomes are expected by Hommes and Sorger (1998) in simulations of the adaptive SAC-learning process:

(i) Convergence to the 'good' steady state equilibrium

(ii) Convergence to the 'bad' steady state equilibrium

(hi) Convergence to the chaotic CEE.

Chaotic CEE occurs when parameters a_t and P_t converge to a constants a* and p* while prices never converge to a steady state (or to a cycle), but keep fluctuating chaotically. This phenomenon is referred to as learning to believe in chaos. Learning to believe in chaos means that the SAC learning dynamics converges to a chaotic system, when a, and p, have converged to constants a* and p*, while prices keep fluctuating chaotically. For Bangladesh trawl shrimp fishery, we simulate the dynamic system (6.8) to (6.10) as adaptive SAC-learning process. We obtain a and p from (6.8) and (6.10) for the given trawl shrimp price of 17 years. Setting the average price as p_0 and values of a and p obtained above as a„, p_0 respectively, we find the initial triple (p_0, a_0, Po) for simulation. Simulated values of a,, and p, are shown in Figures 6.9 and 6.10. Fluctuations in prices are shown in Figure 6.11. It is observed that price initially, upto approximately 25th time period, fluctuates chaotically and then settles down to a stable steady state. The stable steady state price p*D9017.24 is at 63rd period. Figure 6.9 and 6.10 shows the parameters (a_t, p,) converging to (a*, p*) = (9017.24, 0.856638). It depicts permanent chaotic price fluctuations with, sample average a* and strongly positive first order autocorrelation co-efficient p*.

Table 6.4 shows the first 10 lags of the sample autocorrelation and partial autocorrelation of 100 observations of the chaotic price series under SAC learning. The first order partial autocorrelation co-efficient is strongly positive. Table 6.5 contains the estimation results of AR (1) model to the chaotic price series of 100 observations implying estimated belief parameters p, =0.856638 and a, = C/(1- p_t) = 9192.415. The forecasting errors are shown in Figure 6.12. •

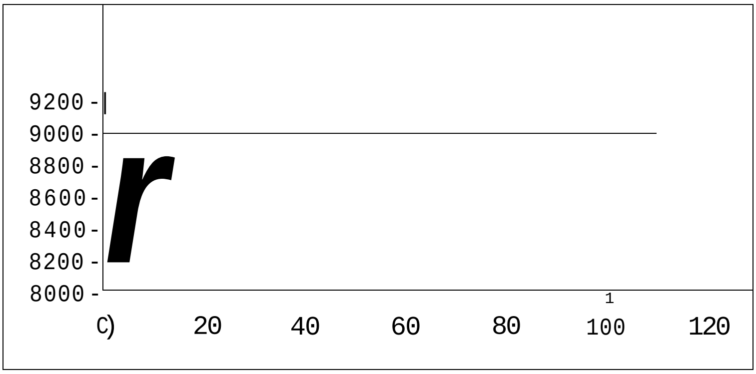

Figure 6.9: Belief Parameters a in SAC learning process converges to constant a*=9017.24

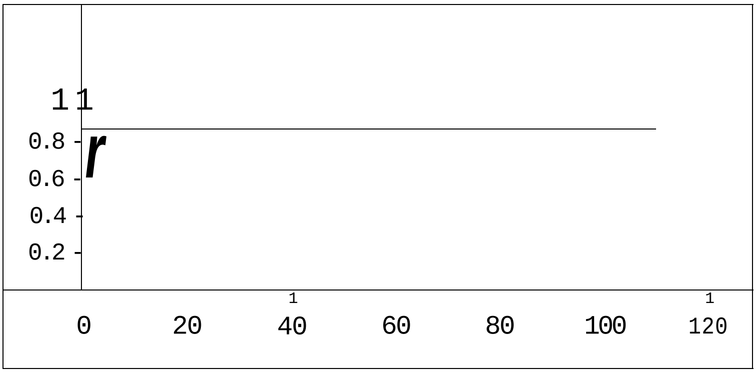

Figure 6.10: Belief Parameters p in SAC learning process converges to constant p"=0.856638

Table 6.4
Autocorrelations, Partial Autocorrelations and Box-Ljung-statistics
of Prices of CEE under SAC Learning

Lag	AC	PC	Box-Ljung-Stat.	Prob.
1	0.857	0.857	74.873	0.000
2	0.742	0.032	131.669	0.000
3	0.610	-0.122	170.468	0.000
4	0.449	-0.206	191.673	0.000
5	0.308	-0.050	201.793	. 0.000
6	0.166	-0.091 .	204.748	0.000
7	0.074	0.088	205.340	0.000
8	-0.008	-0.026	205.347	0.000
9	-0.081	-0.066	206.077	0.000
10	-0.167	-0.192	209.213	0.000

Table 6.6 contains the first 10 lags of the sample autocorrelation, together with their Box-Ljung-statistics of the residuals of the fitted AR(1) model. The autocorrelation co-efficients of the residuals *of* the fitted AR (1) model are *not* statistically significant and the Box-Lunge-statistics indicate that the null hypothesis that prices follow a stochastic AR (1) process can not be rejected.

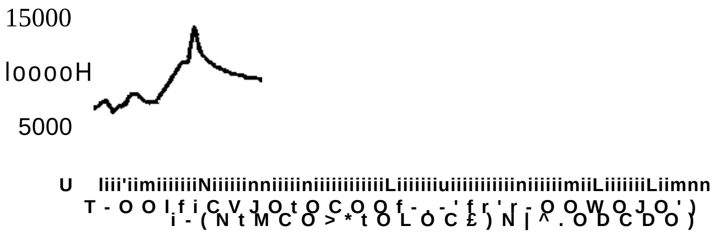

Figure 6.11: Chaotic Prices in SAC Learning Process Shows Gradual Movement Towards Stability

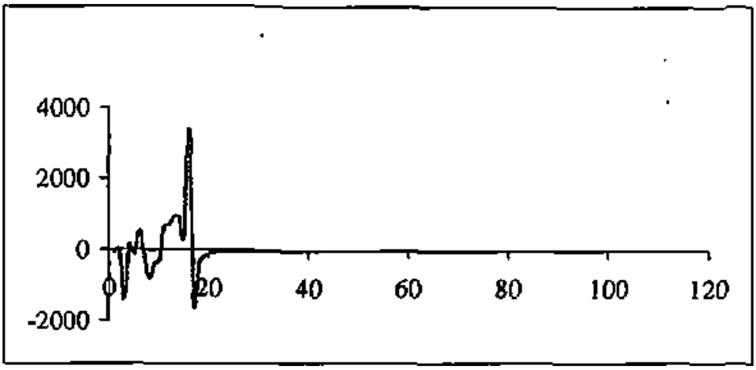

Figure 6.12: Forecasting Errors in SAC Learning Process Shows Chaotic Behaviour at Initial Phase

Table 6.5

Estimation Results for AR (1) Model on Chaotic CEE

Model $p_t = C + \rho p_{t-1}$. ($C = \alpha(1-\rho)$)

Variable	Co-efficient	Std. Error	t'Statistic
C	1317.843	414.1436	3.182092
ρ	0.856638	0.045652	18.76441
R -squared	0.784014		
Adjusted R squared	0.781787		
S.E of regression	450.8387		
Durbin-Watson stat	2.08987		

Table 6.6

Autocorrelations, Partial Autocorrelations and Box-Ljung-statistics of Residuals of Fitted AR (1) Model on CEE under SAC Learning

Lag	AC	PC	Box-Ljung-stat.	Prob.
1	-0.045	-0.045	0.207	0.649
2	0.151	0.149	2.559	0.278
3	0.010	0.023	2.570	0.463
4	-0.029	-0.052	2.660	0.616
5	0.025	0.017	2.727	0.742
6	-0.132	-0.121	4.589	0.598
7	-0.056	-0.074	4.926	0.669
8	-0.138	-0.112	7.009	0.536
9	-0.008	0.005	7.016	0.635
10	0.049	0.084	7.289	0.698

Hence, based on this linear statistical analysis, a careful boundedly rational economic agent would not reject the null hypothesis that prices follow an AR (1) process. Thus the economic agents/planners will be able to successfully follow an underlying dynamics in Bangladesh trawl shrimp fishery. Thus the possibility of jumping to unstable steady state equilibrium and occurrence of catastrophic discontinuities may be ruled out if economic agents involved in Bangladesh trawl shrimp fishery behave rationally and try to understand the true dynamics of shrimp stock.

6.5 Concluding Remarks:

The supply curve of Bangladesh marine shrimp fishery is found backward bending with non-zero discount rate. The extent of bending increases with the increasing value of discount rate. As it is known that backward bending supply curve may cause multiple equilibria and the shifting of demand may result in sudden jump to a new equilibrium position, there exists a possibility of catastrophic discontinuities. Thus, the chaotic dynamics and catastrophic discontinuities of Bangladesh trawl shrimp fishery have been studied under consistent expectations equilibrium (CEE) paradigm. Rational expectations hypothesis (REH) being found extremely stringent for the reason of underlying implicit requirement of perfectly complete information set, the consistent expectations equilibrium (CEE) is considered as more plausible through self-fulfilling mistake under adaptive learning process. The study finds the following:

(i) A linear demand curve being fixed with the intercept where price is minimum and supply equals to MSY, the appropriate slope of the curve, for which the demand curve is a tangent bifurcation of the backward bending supply curve, is determined.

(ii) The study finds that the critical values of the discount rate (5*) is appropriately equals to 12 percent. The dynamic system of Bangladesh marine shrimp fishery has a unique equilibrium point when 5 < 6* and has multiple equilibria when 5 > 6*.

(iii)Dynamics of the system under the process of expectations forming with naive assumption regarding price of economic agents show that the agents be able to learn that their expectations are 'systematically wrong'. Thus adaptive learning process even under naive expectations hypothesis proves that agents can improve their forecasting gradually by incorporating additional observations.

(iv)The mode! of the dynamic system for Bangladesh trawl shrimp fishery shows that the system converges to a ,'good' CEE with all parameters (p, a, p) converging to constant steady state value. Price initially fluctuates chaotically and then settles to a stable state. Thus the fluctuations of the parameters of Bangladesh trawl shrimp fishery, like, stocks, harvests and efforts are deterministically chaotic. If the economic agents follow SAC-[earning process with AR(1) belief described by the parameters a and p, the system converges to 'good' CEE. Values of the belief parameters a and p are found to be steady with highly positive autocorrelation. Autocorrelations of residuals of fitted AR(1) model on CEE under SAC-learning are found insignificant.