

BINARY CHOICE MODELS WITH AVERSION TO INEQUALITY. INDIVIDUAL INTERACTIONS VS. MEAN-FIELD INTERACTION

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PRZEGLĄD
STATYSTYCZNY
Nr 17(23)

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ISSN 1644-6739
e-ISSN 2449-9765

DOI: 10.15611/sps.2019.17.04

JEL Classification: C2, D7, D9

Abstract: For several decades the problem of common goods has been intensively discussed and studied not only by economists, but also by politicians. One particular field of study concerns the problem of social choices realized by collective decisions, or rather individual decisions within some social collective (group). Several analytical models of using common-pool resources are proposed. Most approaches adopted within welfare economics are restricted to the maxim of this part of economics, i.e. to the maximization of the utility function. It was however discovered a long time ago that social interactions may play a significant role. In particular, aversion to inequality can be taken into account as the quantitative manifestation of the human sense of justice. Based on a simple binary choice model it is shown in this paper that by including social interactions into the decisional system of using a common-good resource, it is possible to reveal many stationary states (system multistability). Some of these stationary states may be more, and some others less beneficial from the global point of view. In this paper we investigate the eventual differences introduced by different forms of interactions between individuals. The status of the so-called mean-field approach is also examined.

Keywords: common-pool resources, binary-choice model, stationary state, multistability.

1. Introduction

For a long time, along with the concept of *homo oeconomicus* there also existed the concept of the “tragedy of the commons”, both having the same background of a pessimistic view of human nature. Within this concept, humans were thought of as creatures caring only for their own narrowly defined (economic) well-being. However, as discoveries from the 1950s revealed, people care about much more than just their material status, which has been clear to non-economists for many centuries, starting from antiquity. As for the downfall of *homo oeconomicus*, Daniel Kahneman is worth mentioning (see e.g. [Kahneman, Tversky 2013]), while to expose the tragedy of the commons to the critique, Elinor Ostrom made a significant contribution (see e.g. [Ostrom 2015]).

The main thing is that individuals take into consideration the choices and outcomes of other individuals not only as co-members of the market but also – and to a high degree – as fellow human beings. In particular, the sense of fairness is very strong. Self-regulation of the use of common-pool resources, especially if the users have strong personal interrelations, are highly efficient and the governance of the commons does not in principle need any outer institutions.

One way of modeling this effect may be including “aversion to inequality” to the individual utility function. Such an approach was used e.g. by Fehr and Schmidt [1999]. Aversion to inequality is often thought as manifesting as an aversion to have less than the others. However, the sense of justice extends this aversion also over having more than others – although to a lesser degree. Maybe not for all individuals, but the same approach concerns having less, as not everybody is envious.

In this paper we employ the binary choice model of making decisions. The binary-choice models have a long and fruitful history (see e.g. [Luce 1959; 2000; McFadden 1973]). The topic of the paper is restricted to the Brock-Durlauf model (BD model, see [Brock, Durlauf 2001; 2007]), modified so as to incorporate the Gini-like inequality aversion part instead of the original squared form of interactions between individuals.

The aim of this paper is twofold. The first is to investigate the difference caused by this modification of the original BD model. The second is to investigate the status of the mean-field approach, which can be applied to the model (and has been applied to the original Brock-Durlauf model to investigate its multistability). The mean-field approach is very useful for the analytical analysis of stationary states, however, like each approximation, it may bring some inaccuracies and even artifacts into play. While the mean-field approach is widely applied in physics (and its results may be verified with the experiments) such verification for social systems would be much more troublesome. Thus, the aim of the paper is to investigate whether the stationary solutions of the model change significantly under the mean-field approximation.

The paper is organized as follows. The next section specifies the binary choice model to be used from now on, that is the model with the utility function of an individual which includes an inequality-aversion term, an “objective” term, describing the material benefits of a particular choice, and a random term. Section 4 investigates the model with a Gini-like inequality-aversion term, and other kinds of interactions are also considered and examined. The possible multistability of such models is found and discussed. In the following section the eventual difference between models with individual interactions and interactions with mean-field is investigated. The final section offers a summary and conclusions.

2. Binary choice model

The basic idea behind such a class of model is quite simple. One supposes that the decision-maker at any time has to choose one of two possible decisions: “yes” or “no”. In the context of using common-pool resources, this can mean to exploit or not to exploit this common resource. The decision taken by individual i in time t , is denoted by symbol $x_i(t)$. If one assumes that the choice to exploit the source will be denoted by 1, while the choice to restrain (not to exploit) will be coded by 0, then: $x_i(t) \in \{0, 1\}$. There is a certain profit associated with both decisions, so it is assumed that the person will compare with which decision his or her profit would be higher.

The current choice of coding $x_i(t) \in \{0, 1\}$ instead of e.g. $x_i(t) \in \{-1, 1\}$ is strictly conventional. As the utility function used here is of an ordinal (not cardinal) character, only the differences of utilities play the role and the results for any coding would be exactly the same.

Such methodology of modeling individuals' decisions is widely applied within the field of sociology where the so-called impact function (e.g. [Holyst, Kacperski 2000; Nowak, Szamrej, Latané 1990]) and threshold models (e.g. [Granovetter 1978]) are used. We will use here utility function methodology. However, it was shown [Ostasiewicz, Radosz, Magnuszewski 2011] that these three approaches (the utility function model, the impact function model and the threshold model) are essentially equivalent. The approach using the utility function is used rather by economists, see e.g. the binary choice model of Brock and Durlauf [2001; 2007].

The description of the model is as follows. Any decision yields some “gain” or profit for decision maker and it will be represented by some utility function $U_i(x_i(t))$. The time will be assumed to be discrete, that is, decisions are made in subsequent time-steps, and thus: $t = 1, 2, 3, \dots$

For the scope of this paper we assumed a simple form of the utility function. A similar form was investigated by Brock and Durlauf [2001]. The utility function is defined in the form of a composition of two parts. One of them represents the “objective” part, denoted as $u_i(x_i(t))$. The second part is intended to represent the subjective feeling of an individual i , comparing his/her own decision with the decisions of all the participants in exploiting common resources. This part will be represented in the form of some function of the following type: $f(x_i(t), \{x_{j \neq i}(t' \leq t)\})$. The third term represents the intrinsic randomness of the system and will be denoted by $\epsilon_i(x_i)$.

The further assumption consists in taking an additive form of these two components. The general form of the individual's utility function is the following:

$$U_i(x_i(t)) = u_i(x_i(t)) + f(x_i(t), \{x_{j \neq i}(t' \leq t)\}) + \epsilon_i(x_i), \quad (1)$$

for $i = 1, 2, \dots, n$, $t = 1, 2, 3, \dots$, and $x_i(t) = 1$ (action) or $x_i(t) = 0$ (no action).

Notation $\{x_{j \neq i}(t' \leq t)\}$ means that function f may in general depend on all values of $x_{j \neq i}$ for time step t and proceeding.

A particular case of this general form is specified in the next section.

3. Binary choice model with Gini-like aversion to inequality

We model here the problem of using a common-pool resource which might be for example a fishery. We adopt a binary choice model, that is, in each time step each individual makes a decision either to exploit this common-pool resource (e.g. to take another fish) or to stop.

The objective part of the utility of an action depends on the “objective” (economic) part, which is constituted by the value of the resource taken (e.g. the price of the fish for which it can be sold on the market). Here we will assume this in a simple form: $u(x_i(t)) = hx_i(t)$, where h is the difference in objective utility gained by choice “1” instead of “0”.

It was shown [Ostasiewicz 2019], that by choosing the proper function of aversion to inequality and applying the methodology of Atkinson (of calculating how would joined utility increase if goods were distributed equally) [Atkinson1970], one may recover some known inequality measures or obtain others possessing interesting properties.

In order to incorporate into a choice model a subjective attitude towards inequality, one should decide about the measure of inequality, and how it could affect the utility of a decision. The simplest case, investigated below, is to choose the Gini Mean Difference as the measure of inequality, and to assume that the greater this measure, the smaller the utility. This is considered here as a kind of aversion to the inequality of the whole group.

That is, as

$$GMD = \frac{1}{n^2} \sum_{i,j} |x_i - x_j| = \frac{1}{n} \sum_i \left[\frac{1}{n} \sum_j |x_i - x_j| \right] = \frac{1}{n} \sum_i GMD_i, \quad (2)$$

which may be disaggregated into “inputs” from the individual items.

Thus, introducing some constant J to allow for modeling the strength of the relative role of aversion to inequality the expression $\frac{1}{n} \sum_j |x_i - x_j|$ may be substituted into (1):

$$U_i(x_i(t)) = hx_i(t) - \frac{J}{n} \sum_{j \neq i} |x_i(t) - x_j(t-1)| + \epsilon_i(x_i). \quad (3)$$

An individual will choose the state for which his/her utility is higher. The utilities for decisions “yes” and “no” have respectively the following forms:

$$U_i(1) \equiv U_i(1; t) = h - \frac{J}{n} \sum_{x_j(t-1)=0} 1 + \epsilon_i(1), \quad (4)$$

$$U_i(0) \equiv U_i(0; t) = -\frac{J}{n} \sum_{x_j(t-1)=1} 1 + \epsilon_i(0). \quad (5)$$

$t = 1, 2, 3, \dots$

It may seem unintuitive that for one choice there exists some “objective” input into utility, while for the other it does not. However, as pointed out above, only the differences between utilities matter. Here, for positive value of h : $u(1) - u(0) = h > 0$. If we choose instead coding $x_i(t) \in \{-1, 1\}$ it would be: $u(1) - u(-1) = 2h > 0$, and the result is essentially the same, as parameter h still has to be estimated for the given data. This would just give a twice as high estimation for one coding than for the other.

The probability that an individual will take an action, $P(x_i(t) = 1)$, is equal to the probability that $U_i(1) > U_i(0)$, thus:

$$\begin{aligned} P(x_i(t) = 1) &= P(U_i(1) > U_i(0)) = \\ &P\left(h - \frac{J}{n} \sum_{x_j(t-1)=0} 1 + \epsilon_i(1) > -\frac{J}{n} \sum_{x_j(t-1)=1} 1 + \epsilon_i(0)\right) = \\ &P\left(\epsilon_i(0) - \epsilon_i(1) < h + \frac{J}{n} \sum_{x_j(t-1)=1} 1 - \frac{J}{n} \sum_{x_j(t-1)=0} 1\right). \end{aligned} \quad (6)$$

Note that in Eq. (3) J is the same for all pairs of individuals. This is equivalent to the implicit assumption that each individual interacts with all the others with the same strength. In more advanced models some other kinds of social networks could be applied, e.g. a small-world network [Watts, Strogatz 1998]. Extending the assumption of equivalence of all individuals, we may assume that $\epsilon_i(0) \equiv \epsilon(0)$ and $\epsilon_i(1) \equiv \epsilon(1)$.

Denoting average choice in time step t by $m(t)$ the following relations are fulfilled:

$$\begin{aligned} P(x_i(t) = 1) &= m(t), \\ \frac{1}{n} \sum_{x_j(t-1)=1} 1 &= m(t-1) \text{ and} \\ \frac{1}{n} \sum_{x_j(t-1)=0} 1 &= 1 - m(t-1). \end{aligned}$$

Denoting the cumulative probability distribution of a random variable $\epsilon(0) - \epsilon(1)$ simply by symbol F , this means that $F(\cdot) = F_{\epsilon(0) - \epsilon(1)}(\cdot)$. Substituting these into (6), one gets:

$$m(t) = F\left(h + Jm(t-1) - J[1 - m(t-1)]\right), \quad (7)$$

that is:

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$$m(t) = F([h - J] + 2Jm(t - 1)). \quad (8)$$

In order to determine the stationary states of (8) denoted by m^* , one should observe that these states are defined by the expression: $m(t - 1) = m(t) = m^*$. Thus:

$$m^* = F([h - J] + 2Jm^*). \quad (9)$$

Formula (9) is a self-consistent equation and its solution (and the number of the solutions) depends on the actual form of distribution F .

Assuming that the random term has a logistic distribution,

$$F(x) = \frac{1}{1 + \exp\left(-\frac{x - x_0}{T}\right)}, \quad (10)$$

with scale parameter x_0 and shape parameter T ,

one gets the following expression for equation (9):

$$m^* = \frac{1}{1 + \exp\left(-\frac{[h - J] + 2Jm^* - x_0}{T}\right)}. \quad (11)$$

As the two possible choices are 0 and 1, x_0 will be chosen as equal to 0.5:

$$m^* = \frac{1}{1 + \exp\left(\frac{[h - J - 0.5] + 2Jm^*}{T}\right)}. \quad (12)$$

The shape parameter T is responsible for the degree of randomness in the system.

For rescaled choices, $x_i \in \{-1, 1\}$, formula (12) could be transformed into the one known from statistical physics as the solution of the Ising model (see e.g. [Landau, Lifshitz 1980]):

$$m^* = \tanh\left[\frac{h + Jm^*}{T}\right].$$

From this solution one can see that the shape of parameter T may be interpreted as an analog to the temperature (on the concept of “social temperature” see [Ostasiewicz, Radosz, Magnuszewski 2011; Ostasiewicz 2009]).

As it is known from statistical physics, this equation – within some range of values of parameters – might have three solutions (see Figure 1).

Multistability is very important for social systems. While the system may stay in two different stable stationary states, it may “stick” in a less beneficial state, as the barrier between this state and a more beneficial state (beneficial from the “outer” point of view, e.g. the ecological one) cannot be overcome. Such a situation results in so-called hysteresis, i.e. that the actual state of the system depends not only on the actual state of

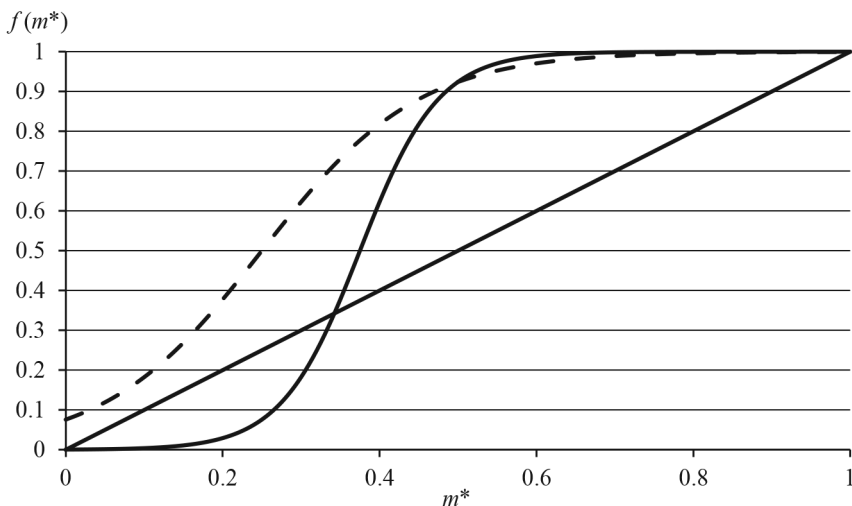


Fig. 1. The different number of stationary state solutions for logistic distribution (intersections of the functions: $f_1(m^*) = m^*$ and $f_2(m^*) = \frac{1}{1+\exp(\frac{(h-J-0.5)+2Jm^*}{T})}$) and the different values of parameters: $J = 2$ (three solutions), $J = 1$ (one solution) and $h = 1$, $x_0 = 0.5$, $T = 0.2$ (both cases)

Source: own construction.

parameters but on its history as well (for a detailed discussion see e.g. [Ostasiewicz 2011], and the literature therein). On the other hand, being in a seemingly good state does not guarantee the “safety” of the situation. Depending on the height of the barrier between the stable stationary solutions, the state may be more or less resilient (see e.g. [Ostasiewicz, Magnuszewski 2011]), which cannot be detected by investigating the state itself.

The phenomenon of multistability and the problem with the degree of the resilience of the system occurs not only with one specific choice of the random term (logistic), imitating statistical physics. For other choices, such as normal distribution, this effect appears as well, see Figure 2 (although the solution cannot be obtained in such a neat analytical form as (12)).

Results (9) and (12) are well known from statistical physics and from solutions of the Brock-Durlauf model. It turns out that for binary choices and for the Brock-Durlauf-like utility function there is no difference whether the interaction term has the form of the Gini Mean Difference or quadratic form (like in the Ising model in physics and the original BD model).

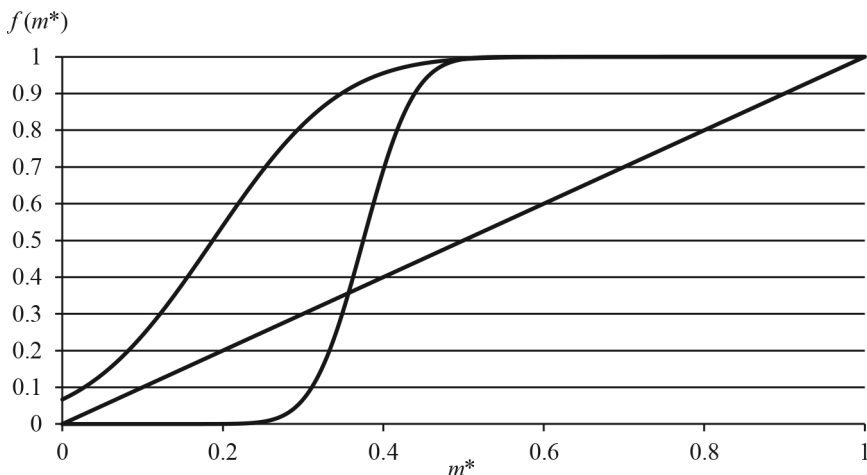


Fig. 2. The different number of stationary state solutions for normal distribution $N(\mu, \sigma)$ (intersections of the functions: $f_1(m^*) = m^*$ and $f_2(m^*) = F_{\text{norm}}([h - J] + 2Jm^*)$) and the different values of parameters: $J = 2$ (three solutions), $J = 0.8$ (one solution) and $h = 1, \mu = 0.5, \sigma = 0.2$ (both cases)

Source: own construction.

It might be tempting to reproduce the above described procedure for other popular inequality measures, however there are two problems. The first one is as follows. As the utility function is of an ordinal character (not cardinal), it would not be proper to use quantities which would depend on the choice of coding: 0 and 1; -1 and 1 or anything else (and most of the inequality measures are not invariant under translation). While this problem could be solved with the proper scaling, the second one flows from the technicalities of measures like the Atkinson measure or the Theil index. Namely, these measures cannot be presented as sums of inputs from particular individuals, but rather from the very beginning have to be treated as representatives of the population as a whole. Thus, they cannot be used in individual utility functions.

Instead of trying to implement some other known inequality measures, another approach not based on popular inequality measures, might be tried. Some other, more complicated functions (more complicated compared to the simple absolute differences) might be suggested as the aversion to inequality inputs to utility.

However it can be easily noticed that all possible forms of additive functions of arguments $\{x_i - x_j\}$ lead to qualitatively the same – up to the constants – results. Indeed, for any quantity defined in the form of the sum $\frac{1}{n} \sum_j f(x_i - x_j)$ one would have:

$$U_i(1) = h - \frac{J}{n} \sum_{x_j(t-1)=0} f(1) - \frac{J}{n} \sum_{x_j(t-1)=1} f(0) + \epsilon_i(1) =$$

$$h - J[f(1)(1 - m) + f(0)m] + \epsilon_i(1), \quad (13)$$

$$U_i(0) = -\frac{J}{n} \sum_{x_j(t-1)=1} f(-1) - \frac{J}{n} \sum_{x_j(t-1)=0} f(0) + \epsilon_i(0) =$$

$$-J[f(-1)m + f(0)[1 - m]] + \epsilon_i(0). \quad (14)$$

Thus, the mean-field stationary state would have the following form:

$$m^* = F([h - J[f(1) - f(0)]] - J[2f(0) - f(-1) - f(1)]m^*), \quad (15)$$

which is equivalent to the expression given by(9) up to the values of the constants.

After this result it is possible to conclude, supposing that all individual are “equivalent” (each individual interacts with all the others with the same strength and the random term for each individual has the same distribution), the results of the binary model defined by individual utility in form (3) with the sum of absolute differences in the second term replaced by the sum of any function $\sum_j f(x_i - x_j)$ are the same up to the constant. Thus, multistability and hysteresis may be observed, similarly to the physical phenomena of the Ising model.

4. Individual interactions vs. interactions with the mean-field

Although we have assumed in the previous section that an individual does not make a difference between one and the other of his/her co-users of a given common-pool, still the interactions are one-to-one, i.e. an individual is “aware” of the particular choices of all the others. The mean-field approach, borrowed from statistical physics, is defined in the following way: one does not interact with individual persons but rather with the averaged choice of all the others.

In some situations this is just an approximation, however in some others it may be justified from the very beginning. Users of some common-pool resources might not be able to trace the conduct of each of the co-users but rather the final joined outcome, e.g. in an office we collect monthly some money for coffee to be used by all the community, and the collection is both voluntary and anonymous. One thus knows only the joined result, and based on this joined result a decision is made either to contribute or not in the next month. At first glance such a change of settings of the model may seem to change the results insignificantly.

However this is not true, as interaction with the mean-field at the very beginning introduces nonlinearity to the model.

First, let us investigate the model within which aversion to the inequality of an individual will be modeled as the square of the difference between his/her decision and the mean outcome of the others. It might be noted that such a choice leads, while going to the utility of the whole population, to another popular measure of inequality – variance. (Here we assume that the population is large enough and the influence of the single individual on the total average might be considered very small. This is more justifiable that while we restrict to the binary choice it is not possible to observe “outliers”, which, in general, might influence the total average to a high degree). The individual utility function reads:

$$U_i(x_i(t)) = hx_i(t) - J[x_i(t) - m(t-1)]^2 + \epsilon_i(x_i), \quad (16)$$

and for the two possible choices:

$$U_i(1) = h - J[1 - m(t-1)]^2 + \epsilon_i(1), \quad (17)$$

$$U_i(0) = -J[-m(t-1)]^2 + \epsilon_i(0). \quad (18)$$

The probability of choosing an action, $x_i(t) = 1$:

$$P(x_i(t) = 1) = P(\epsilon_i(0) - \epsilon_i(1) < h - J[1 - m(t-1)]^2 + J[-m(t-1)]^2). \quad (19)$$

Assuming identical distributions of random term for all individuals and denoting it by F :

$$P(x_i(t) = 1) = F(h - J[1 - m(t-1)]^2 + J[m(t-1)]^2) = F([h - J] + 2Jm(t-1)), \quad (20)$$

thus, again getting the same stationary states as in (9).

However, assuming more complicated forms of interactions, e.g. fourth power:

$$U_i(x_i(t)) = hx_i(t) - J[x_i(t) - m(t-1)]^4 + \epsilon_i(x_i), \quad (21)$$

the stationary states would be in the form:

$$m^* = F([h - J] + J[4m^{*3} - 6m^{*2} + 4m^*]). \quad (22)$$

Remembering, that for individual interactions the stationary state would be described by:

$$m^* = F([h - J] + 2Jm^*),$$

let us compare the results.

The graphical representation of the solutions for some chosen values of parameters are presented below (for logistic distribution of random term) in Figure 3.

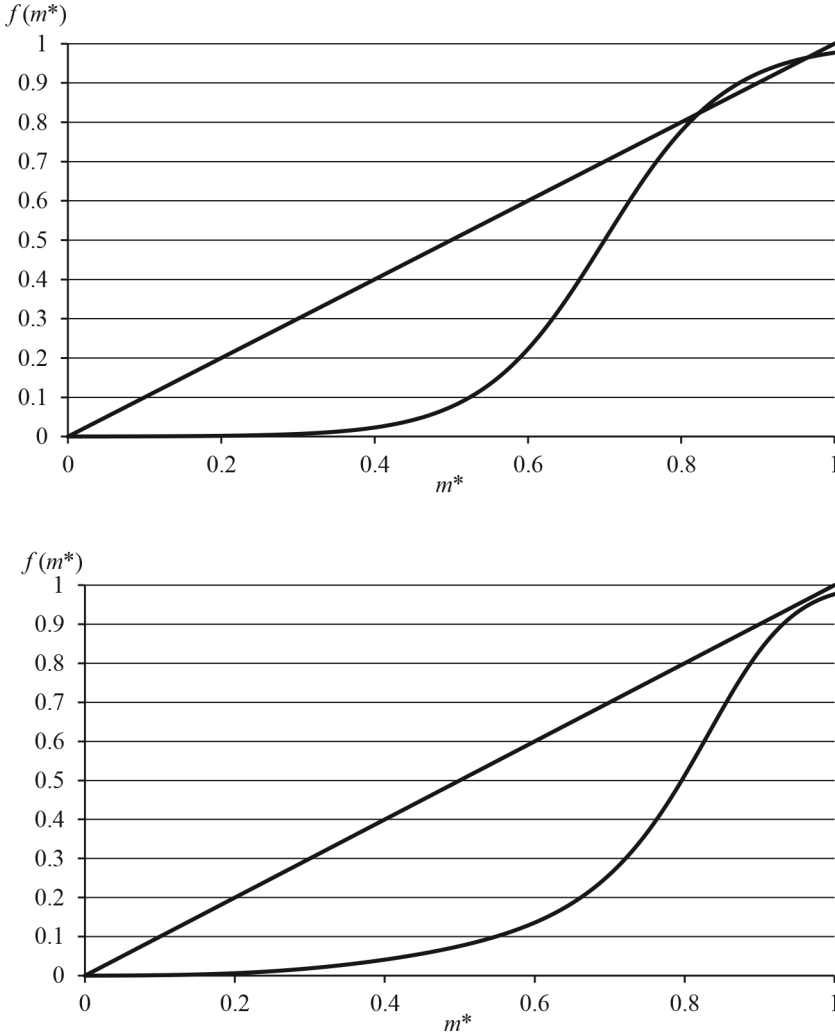


Fig. 3. Graphical solutions for stationary states for individual interactions ($f_1(m^*) = m^*$, $f_2(m^*) = F_{\log}([h - J] + J[4m^{*3} - 6m^{*2} + 4m^*])$) (a) and mean-field interactions ($f_1(m^*) = m^*$, $f_2(m^*) = F_{\log}([h - J] + 2Jm^*)$) (b). $h = 0$, $J = 1.25$, $x_0 = 0.5$, $T = 0.2$

Source: own construction.

It may be seen in Figure 3 that the choice of mean-field interactions instead of individual ones might influence the very existence of some solutions. For the chosen values of parameters for individual interactions

there exists the “high use” stationary solution (m close to the maximum value of 1) while for the mean-field interactions the only stationary state is the “low use” one, close to 0.

5. Conclusions

According to recent field observations, it is crucial to include social interactions into modeling using common-pool resources. The sense of justice, which may be expressed as an individual’s aversion to inequality, seems to be an inherent part of human nature. Taking into account only egoistic economic interest, everybody would use the common pool to the maximum of his/her ability. However, including social interactions into the picture may change qualitatively this situation. There might appear more beneficial – from the global point of view – stationary states characterized by the “low use” of the common resource.

The question is, how to model these social interactions properly.

The answer to this question is not easy. Each situation should be examined individually, as each real problem is determined by many restrictions which have to be taken into account when constructing the model.

In this paper we investigated two particular issues.

First, it appears that within one-one interactions and binary choice, all models defined by individual utility in the form (3) and interactions given by the sum of any function $\sum_j f(x_i - x_j)$, give the same results, up to the constant.

The second conclusion is that for most forms of interactions, there is a difference between modeling individual interactions and interactions the with mean-field. At first glance this difference might seem not so important. Indeed, knowing the mean choice, one may deduce how many co-users have chosen 1 and how many have chosen 0. However, for nonlinear interaction – function f is more complicated than the absolute difference or square of the difference – it obviously does not hold $\sum_j f(x_i - x_j) = f(x_i - \sum_j x_j)$, and thus the results may be qualitatively different. As was pointed out above, in some situations the mean-field approach is the best one for the given problem, however in other situations it has to be regarded as an approximation only and the results obtained within this approach might be misleading, even in a qualitative way.

Acknowledgements

The author is highly indebted to the anonymous referees whose remarks and suggestions helped to improve this paper significantly.

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**MODELE BINAREGO WYBORU UWZGLĘDNIAJĄCE AWERSJĘ
DO RYZYKA. ODDZIAŁYWANIA INDYWIDUALNE
VS. ODDZIAŁYWANIA ŚREDNIOPOLOWE**

Streszczenie: Od kilku dekad zagadnienie użytkowania dóbr wspólnych jest intensywnie badane i dyskutowane z punktu widzenia nie tylko akademickiego, ale i politycznego. Jednym ze szczegółowych zagadnień jest kwestia podejmowania indywidualnych decyzji w kontekście całej grupy (zatem decyzji innych osób). Proponowane są różne modele użytkowania dóbr wspólnych. Większość z nich opiera się na metodyce maksymalizowania indywidualnej funkcji użyteczności. Jednakże, co odkryto już dawno temu, również oddziaływania społeczne mogą odgrywać tu istotną rolę. W szczególności może to być awersja do nierówności jako ilościowe ujęcie ludzkiej potrzeby sprawiedliwości. Na podstawie prostego modelu binarnego wyboru pokazano w niniejszej pracy, że w modelu użytkowania dóbr wspólnych z uwzględnieniem interakcji społecznych może wystąpić wiele możliwych stanów stacjonarnych. Różne z nich mogą być mniej lub bardziej pożądane z globalnego punktu widzenia. W pracy brane są pod uwagę różne postaci oddziaływań społecznych. Badany jest również status tzw. przybliżenia średniego pola, czyli oddziaływań jednostki nie z indywidualnymi jednostkami, lecz z uśrednionym „polem” stwarzanym przez resztę zbiorowości.

Słowa kluczowe: dobra wspólne, modele binarnego wyboru, stany stacjonarne, multi-stabilność.