"Babeş-Bolyai" University
Cluj–Napoca, Romania
Faculty of Physics

Ph.D Thesis Summary

Computational and analytical study of collective biological and social phenomena

Advisor: Prof. Dr. NÉDA ZOLTÁN

Káptalan Erna-Katalin

Referees: C.P. I GHEORGHIU EUGEN
Prof. Dr. SZABÓ LÓRÁND
Conf. Dr. BURDA IOAN

Cluj-Napoca
2011

Keywords: collective phenomena, forms of collective behaviour, optimization induced synchronization, spring-block model, highway traffic, random networks.

Contents

Introduction

Collective behaviour is a booming field of research, with many interesting implications and practical application possibilities. The field is of truly inter- and trans-disciplinary character, since collective behaviour is present in all domains of sciences: economics social sciences, biology, ecology, physics, chemistry and even engineering. The aim of the present thesis is to give a unified view on this very broad subject without attempting however to achieve a complete and exhaustive description. After a brief historical and bibliographical review we present some personal contributions in the field, which exemplifies the interdisciplinary character of such studies. We use classical models and methods of statistical and computational physics, for modelling and understanding classical collective phenomena from biology, sociology and physics.

The most well-known form of collective behaviour in biology is spontaneous synchronization. Most of our studies focuses thus on this phenomena which is also present in social and physical systems as well. Our contribution in this field is made by realizing numerical and experimental studies for a novel synchronization paradigm which is based on optimization dynamics. This novel approach has the potential to explain several synchronization phenomena in a very elegant manner.

As a second study we have considered a simple physical model to approach a complex collective phenomenon from our every-day life: highway-traffic. Highway traffic can be modelled with several agent-based models, but our approach here is different and we consider the very general spring-block slip-stick model family to understand collective behaviour in this system.

Finally we consider some studies in the booming field of social networks. Social systems are usually governed by their underlying network structure. Collective behaviour in such systems are governed thus also by this network topology. Within the present thesis we consider also a model study in such perspective, investigating and modelling a large social network: the Erasmus student mobility net. By investigating this network we map and model the university staff's professional collaboration connections and the way this is reflected in student mobility.

Collective phenomena can be regarded as the theory of connectivity: one finds connections and interactions among the components of the system; mutual influence and interaction between the system and its environment, analogies and basic guiding principles for different phenomena.

As a practicing high-school physics teacher this field proved to be well-chosen and very enlightening to me. During my PhD studies I found that is important to make my students observe and deliberately seek connections between seemingly distant phenomena. Natural phenomena, economical or social life are all complex. In order to perceive them, the coming generation has to be able to grasp the essence of a phenomenon, to find the connections, to make a synthesis, and to use basic principles and analogies. A transdisciplinary approach of collective phenomena can help improving cognitive abilities of children, raise their interest for investigating nature and stimulate their innate creativity.

The structure of the thesis

The thesis is structured in two parts. The first part contains a bibliographical study of collective phenomena and its major forms. The second part deals with modeling collective phenomena, and presents the original contributions related to three different topics:

1. Synchronization in a new perspective.
   Our publications related to this topic appeared in *Journal of Physics*, *International Journal of Bifurcation and Chaos*, *Fizikai Szemle*, and in in four conference proceedings.
2. The use of spring-block models for describing various collective phenomena, focusing on highway traffic.
   Our contributions were published in *Journal of Control Engineering and Applied Informatics* and a conference proceeding.
3. The importance of networks in understanding collective behavior in social systems.
   Our related study was published in *Physica A*.

The thesis contains 53 figures and a bibliography composed of 101 references.

A brief review of Part I

Part I contains a brief introduction about collective phenomena in sociology, biology and physics and an attempt of identifying the main forms of collective phenomena.

In its classical meaning, "collective behaviour" is an alternative to crowd behaviour (the case when a great number of anonymous, interacting individuals face one common issue and act in a totally different mode from what they would have done individually [1]. In these situations people do not use their complex cognitive abilities: responsibility of individuals vanishes, ideas or emotions spread through the crowd like contagion. The group will act as a single being under the influence of the emerging "collective mind". Actions like riots, revolts, rebellions, lynches, campus unrest, or emergence of panic in case of fire or calamity, civil right or social reform movements, disaster cycles, social epidemics, religious or nationalistic movements, terror, propaganda, emergence of fads, crazes, hearsay, gossip, rumour, memes, media hypes or shifts of the public opinion can all be considered collective phenomena in sociology [1–3].

On the other hand, many living creatures seem to act guided by a "hidden intelligence" (flock of birds, herds of migrating ungulates, swarms of bacteria, bees or ants) but it was shown, that their complex activity is guided by very simple rules. Order emerges as a result of simple interactions among these living entities. The resemblance between behaviour of human crowds and group-living animals is easy to accept, but nature offers many other examples for systems formed by many interacting entities behaving totally different than its components would. Circadian rhythm of living entities, synchronous flashing of some firefly species, emergence of order in case of a honeycomb or a termite, or the amazing fractal structures of plants or patterns on the coats of mammals (stripes on a zebra or tiger, spots on a jaguar) are examples for collective behaviour in biology [4–7].

Systems with a big number of tiny interacting components, which together produce effects on large scale are familiar to physicists, but most of these phenomena had special names in physics and specific models of their own. Many-body problems, pattern formation of vibrated granular matter, emergence of fingering, vortices or avalanches, segregation, phase-transition, magnetization, crystallization and synchronization phenomena can all be considered collective behaviour. Physics dealt with collective phenomena and owned the tools of investigating such systems much earlier than "collective behaviour" as an interdisciplinary field was even born [8, 9].

Different sciences met collective behaviour in different situations. They named them, studied them and tried to model them. This is why we can find a multitude of expressions which belong to the collector concept of collective behaviour: crowd behaviour, self organization, emergence and dynamic of networks, collective adaptive systems, trail formation, pattern formation, synchronization, self-organized criticality, cellular automata, phase transition, cluster formation, avalanches, a.s.o. Great minds not only recognized these similarities, but also tried to find connections among them. There have been many endeavours to describe different manifestations of collective behaviour with more or less success. Nowadays, the tendency is to group the similar phenomenon of different sciences according to the mechanism and the model which describes their dynamics. There can be considered two main groups of collective phenomena: the first group would gather all synchronization phenomena and the second would contain all forms of self-organization and pattern formation (including trail formation, segregation, avalanches, cellular automaton, self-organized criticality, a.s.o.). Some features of collective phenomena, such as the network structure, the emergence of scale-free distribution or phase transition could be met in many cases of collective behaviour. These features usually are the hint of the system's complexity.

Given the broad variety of collective behaviour and the multitude of models used in the description of the same phenomenon, we have chosen to present only some representative phenomena and models.

Review of Part II

Part II contains the original contributions in three different topics: modeling synchronization, modeling complex phenomena with spring-block models and using networks to approach complex systems.

Emerging synchronization

The most well-known form of collective behaviour in biology is spontaneous synchronization, namely the case when a huge number of components spontaneously "agree" upon a rhythmic activity without having any central leader or constraint. Most of our studies focuses thus on this phenomena which is also present in social and physical systems as well. Well known examples are the circadian rhythm of living organisms, "sympathy" of two pendulum clocks synchronization of two organ-pipes, synchronous flashing of fireflies, synchronization of quantum oscillators, the emergence of rhythmic applause or synchronization of pedestrian walk) [10, 11].

In a system of oscillators synchronization emerges as a result of interactions between the components. In order to find out under which conditions synchronization appears, models are needed. According to the type of the interaction that makes possible the synchronization of the system we can talk about three model-categories: phase-coupled oscillator models, pulse-coupled oscillator models, and optimization induced multimode integrate and fire stochastic oscillator models.

The *phase-coupled oscillator model* proposed by Kuramoto and Nishikava considers all-to-all coupled oscillators with different own frequencies. Synchronization of the entities is considered to emerge as a result of a continuously acting phase-pulling interaction forces between the oscillators [12].

The *pulse-coupled integrate and fire model* was first introduced by Ch. Peskin and refined by Strogatz and others. This model resembles two characteristics of biological oscillators: their pulsatile mode of operating (after emitting a pulse they have a longer inactive period) and their non-continuous interaction (a pulse emitted by one oscillator will trigger those being close to their own firing stage) [13].

The *optimization induced stochastic oscilator model* introduced by Z. Néda and his colleagues considers integrate and fire oscillators having different and fluctuating periods. The most amazing thing about the optimization induced stochastic oscillator model is, that there is no direct interaction between the oscillators, but even in these conditions synchronization emerges [14, 15].

The first thing that makes this model so different from others is the fact that an oscillator can have more modes of oscillation. The period of such an oscillator has three stages $A \to B \to C \to A \to \ldots$ An oscillator will not emit any signal in stage A and B, but emits one in stage C.

The time-length of the first (A) part (τ_A) is the stochastic part of the period and its average value is τ^*. The second, B, part is the longest part of the total period, and its length can take more values (τ_{BI} or $\tau_{BII} = 2 \cdot \tau_{BI}$ in the simplest case of two-mode oscillator) (Figure 1). The oscillators "are working" in order to keep a desired f^* pulse intensity. At the end of stage A every oscillator compares the total f output of the system with the desired f^* output level, and will choose accordingly between the two modes of oscillation: It will work in the shorter, B_I mode if in that moment the total intensity is not strong enough ($f < f^*$), and it will choose mode B_{II} if the total output is higher than the optimal intensity level ($f > f^*$). Shifting between the two possible modes will realize the optimization of the output signal, and implicitly will guide the system toward synchronization.

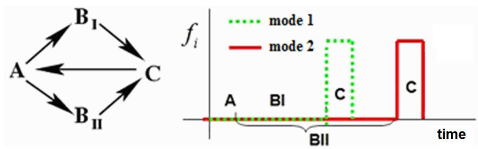

Figure 1. Possible dynamics of the two- mode stochastic oscillators.

Surprisingly, despite of the frequency differences among the oscillators, and despite of their fluctuating own periods, the system will become partially synchronized for a relatively wide interval of the f^* desired value. In this case synchrony emerges in the system without the existence of a phase-difference minimizing effect, as a by-product of a simple optimization rule.

Computer simulations of the model made by Z. Néda and R. Sumi [16] showed, that in case of globally coupled oscillators synchronization emerges for an interval of the desired f^* signal strength if the τ^* stochasticity is fixed. As the number of components grows, the emergence or disappearance of synchronization takes place more and more abruptly, as a phase-transition. For given values of f^* signal strenght and τ^* stochasticity, the periodicity of the system grows together with the N size of the system. For local coupling in a 1D topology the periodicity level of the system does not depend on the number of oscillators, but it has an interesting step-like shape and the number of steps depends on the number of interacting neighbours.

The optimization induced synchronization model describes well several synchronization phenomena, but every case is special. So we searched for some applications of the model which would present interest in case of biological oscillators. We identified two such directions of study: stochastic oscillators arranged in a CNN-type topology, and stochastic integrate-and-fire oscillators which can choose different signal length. For both of these directions the theoretical and computational study was made and counter-checked using an experimental device.

1. First we considered locally coupled two-mode stochastic oscillators arranged on a 2D lattice [17], because the CNN-type topology (CNN=Cellular Neural Network) is a realistic assumption especially in the case of biological oscillators.

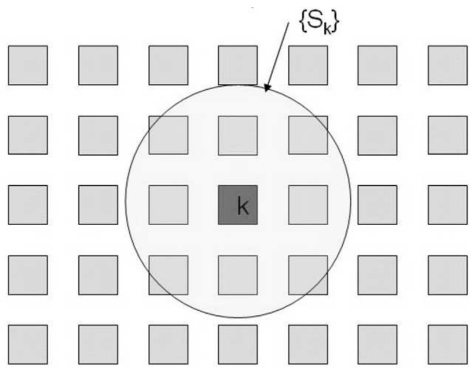

Figure 2. Interaction topology of the considered oscillators.
Here $\{S_k\}$ means the neighbourhood of oscillator k [17].

As shown in Figure 2 the k^{th} oscillator "feels" the presence of the first S nearest neighbours, so detects the sum of pulses emitted by its close neighbourhood.
The dynamics of the system is similar with the case presented in the former section. Our aim was to find out whether this system produces the same behaviour as the globally coupled system: more precisely whether the periodicity enhancement is a specific feature of oscillators coupled in CNN-type architecture or not.
Computer simulations were done for different number of neighbours ($S = 8$, 12 and 20) and different (N=LxL) system sizes. As we can see on Figure 3, for a small number of neighbours the periodicity enhancement is not convincing but in the case of more neighbours the periodicity enhancement is clearly produced for a broad interval of the f^* value. The periodicity of the system increases with the number of components, as in the globally coupled case.
Representing the periodicity level as a function of the desired f^* signal strength, in the case of two-dimensional system the same "stairs" can be noticed as in the case of a system arranged on a 1D lattice, and the number of steps grows with the number of interacting neighbours.

2. As a second direction of study related to synchronization phenomena we constructed an alternative of the presented two-mode stochastic oscillator model. The two mode stochastic oscillators presented previously were capable of emitting signals with the same fixed pulse length. Those two modes had different inactive periods. It is worthy studying another version of the two-mode oscillator model (model II), where the unlit or inactive part of the period is invariant, and the two modes differ by the length of the signal emitted.
The period of model II oscillators has the same three stages as model I, emitting a signal only in its C stage. In the original model the modes of oscillations were defined by the time-length of the inactive state. For model II the length of stage B is fixed, and the two modes will be distinguished by the time-length of the active, C stage. Figure 4 sketches the difference between this model II and the model I (model I is

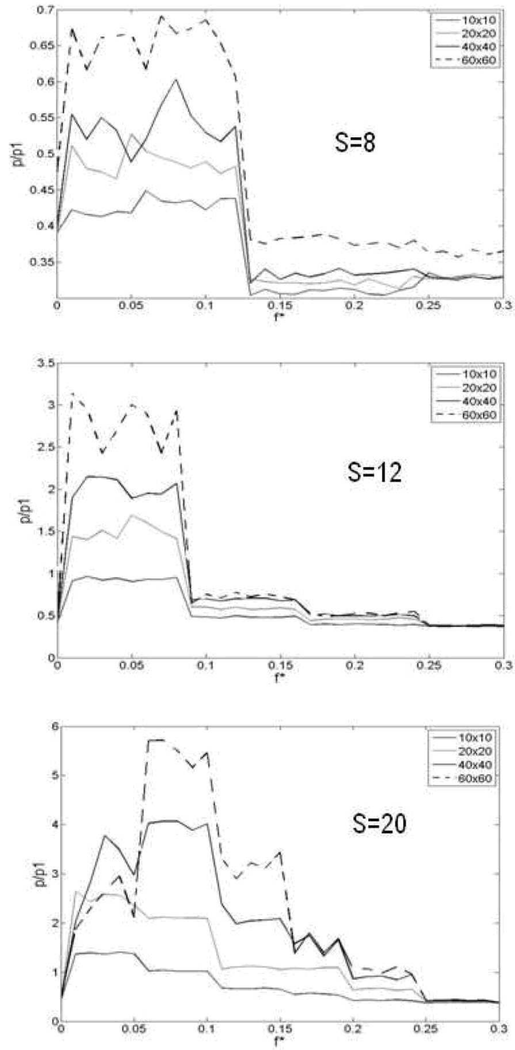

Figure 3. Periodicity of the locally coupled system as a function of the f^* threshold. Results for different interaction neighbourhood (quantified by S) and lattice sizes as indicated in the legend ($\tau^* = 0.2$ for all the cases) [17].

the original two-mode stochastic oscillator model).

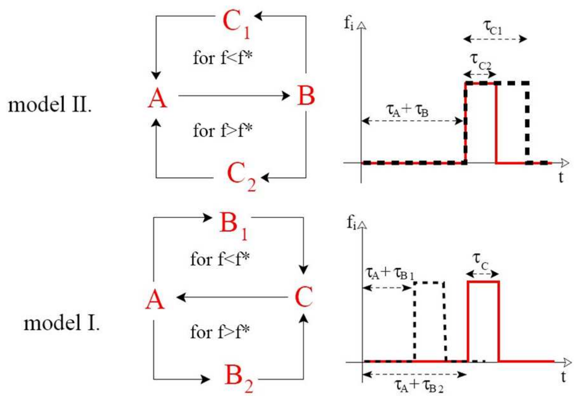

Figure 4. Sketch of the dynamics of the two different multimode oscillator models, and their output signals as a function of time [18].

Due to this small difference the optimizing dynamics of model II will be also different: When an oscillator detects lower output intensity ($f < f^*$) than the desired f^* value, it will "decide" to choose mode $C1$ emitting a longer signal in order to increase the total output intensity level. When the output of the system is bigger than the desired value ($f > f^*$), the oscillator will work in the shorter mode (emitting a short signal) in order to decrease the average pulse intensity.
Computer simulation for a system formed by model II oscillators showed that for too small or too big f^* values synchronization does not occur, but at a fixed τ^* value of the stochasticity synchronization emerges for a finite interval of the desired f^* intensity (Figure 5). It is interesting to observe, that for a fixed stochasticity level of the system the order parameter depends upon the desired f^* value: the interval which permits synchronization narrows down for higher levels of τ^* stochasticity. (The more stochastic the system is, the higher threshold-sensibility it has.)
Synchronization level as a function of f^* was also investigated for the case of global and local coupling (Figure 6.a, b). An attentive observation of Figure 6 leads us to the conclusion that global coupling is the best chance for emerging synchrony.
Computer simulations also showed, that for fixed values of τ^* and f^* but different number N of elements the synchronicity level increases monotonically with the number of units in the system, as in the case of model I. Considering more and more units the appearance and disappearance of synchronization happens more and more abruptly, in agreement with what one would expect for a phase transition-like phenomena. So threshold-sensitiveness also grows with the number of oscillators in the system. It is important to notice that similarly with the case of model I, the synchronization level (p) of the ensemble is better than the synchronization level of one isolated unit (p_1) working in the long period mode, so more oscillators in the system mean a better periodicity.

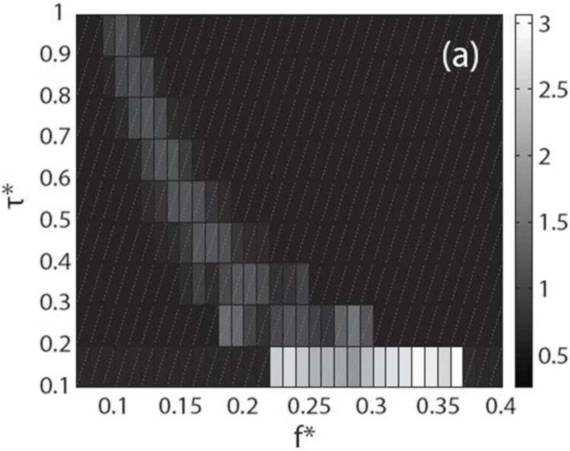

Figure 5. Synchronization level of the system in function of τ^* and f^* (). The value of the order parameter is represented using different shades of grey. The lightest gray means highest p/p_1 order parameter [19].

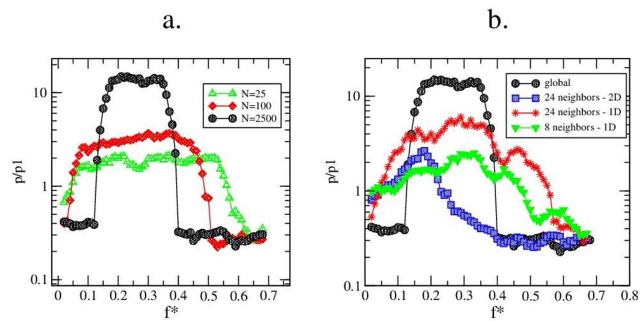

Figure 6. Synchronization level as function of f^*.
a). for globally coupled model II oscillators (for 25, 100 and 2500 units) and
b). for 2500 oscillators coupled globally and 2500 oscillators coupled locally arranged on a 1D or 2D lattice [20].

3. In order to get a reinforcement of our results obtained by computer simulations, experimental studies were also made. My colleagues, Sz. Boda and A. Tunyagi have realized a setup of programmable electronic fireflies, so we had the opportunity of using it.
   These electronic fireflies (Figure 7) are integrated circuits having a simple circuit diagram. Each has a *micro-controller* (programmed to work as model I or model II

oscillators) a photoresistor (which detects the light in the system) and a light emission diode (this gives the output of the oscillator).

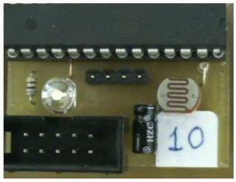

Figure 7. Picture of the electronic bugs and sketch of the main electronic parts [17].

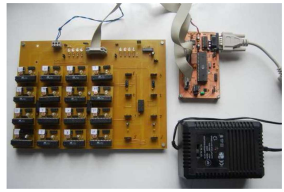

Figure 8. Circuit board with the electronic fireflies and the computer interface [17, 18].

The electronic fireflies are placed on a circuit board (Figure 8) connected to a PC, which can gather information about the light intensity emitted by the system and the state of the units, saving all the relevant information in a file.
We compared systems formed by model I and model II oscillators. The results for N=9, 16 and 22 oscillators in the system can be seen on Figure 9.

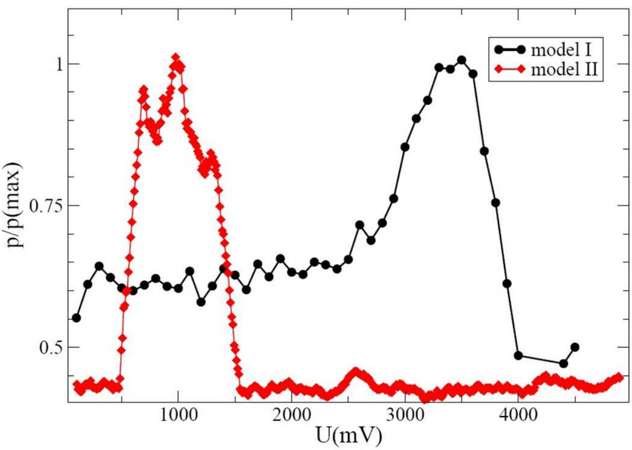

Figure 9. Experimental results obtained for 16 coupled electronic fireflies. Results for both model I and model II (parameters for model I: $\tau_{B2} = 2 \cdot \tau_{B1} = 1536$, $\tau_C = 384$; parameters for II: $\tau_{C1} = 2 \cdot \tau_{C2} = 384$, $\tau_B = 768$) [20].

The experimental results confirmed all the major predictions of the numerical simulations. Both curves show a qualitatively similar trend. In both cases there is an interval of the U reference voltage (the correspondent of the f^* desired intensity value), where the synchronization level strongly increases. Synchronization level

grows monotonically with the number of oscillators in the system. As it was expected, in the case of model II the interval of the output level where synchronization occurs is shifted towards the lower values of the f^* parameter.
The studied systems offer wide possibilities for technical applications as well. Such systems could be useful for detection purposes and such a system of non-pefect coupled two-mode oscillators can act as a reliable oscillator with stable period. This is a clear, fault-tolerant behaviour, which allows to engineer oscillators with very stable periods using imperfect units.

Using the spring-block model for collective behavior in highway traffic

The spring-block or Burridge-Knopoff model took birth as a model of earthquakes. The tectonic plates involved in the generation of the earthquakes are modeled by two surfaces connected through a row of blocks. The blocks are interconnected by springs and connected to the upper surface with springs as well. The upper surface is dragged with a constant velocity and the blocks slide on the rough bottom surface with friction. As a result of the stochastic friction forces the blocks will slide in avalanches following the motion of the upper surface.The avalanches generated by the slide of the blocks correspond to earthquakes. The energy dissipation through these avalanches has a power-law distribution, so this simple one-dimensional model reproduces with success the empirical Guttenberg-Richter-law.

Due to the spectacular evolution of computers and computer simulation methods this simple mechanical model proved to be useful in describing various other physical phenomena as well. Paint or mud usually dries forming specific tiny polygonal "islands". Patterns formed by these dried granular materials can be reproduced using the spring-block model [21]. Nanosphere and nanotube structures have a wide applicability in today's engineering. These tiny components cannot be assembled manually: capillarity driven self-assembly is used, a novel and intelligent technique based on the principles of collective behaviour. This mechanism can be also modeled by the spring-block model [22]. Although magnetization process of the ferromagnetic material is a pretty complex phenomenon, a simple spring-block model reveals the avalanche-like steps of this disorder-driven phase tranzition [23]. The spring-block model can be also used to reveal the emergence of geographical space-like partitions [17].

Here we present an interesting application of the spring-block model: simulation of the traffic on a highway with only one traffic lane [24, 25]. Highway traffic can be modelled with several agent-based models, but our approach here is different and we consider the very general spring-block slip-stick model family to understand collective behavior in this system.

In our model the blocks are representing the cars in the row, and the springs are modelling the distance-keeping interactions between the cars. These are irrealistic springs, with one-directional forces: the car in front has an effect on the one behind it, but no reaction force exists (Figure 10).

The inertia of drivers is modeled by the static F_s and dynamic F_d friction forces between the cars and the plain beneath, where $F_s > F_d$. The ratio between dynamic and static friction forces $F_d/F_s = f$ had the same value, (f=0.6) for all the simulations. These

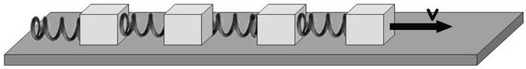

Figure 10. The spring-block chain considered for modeling idealized highway traffic on one lane.

"friction forces" have a normal distribution with a fixed mean value (F_m), and standard deviation (σ). In case of a new location of one block a new static friction force is generated, and the corresponding dynamic force is also updated. The differences between driving attitudes and their fluctuations in time are both included in friction forces, so the standard deviation of the friction forces becomes one of the most important parameter governing our simulations.

The blocks are labeled after their ordinal number, j, and their order remains the same in the simulation. At the start the "cars" are arranged on a lane at the same, l_0 distance one from another, so all the springs are in equilibrum. At the start the positions of the blocks are expressed as $x_j(0) = -j \cdot l_0$, and the distance they made in the previous time-step is, for all cars $d_j(0) = 0$. Simulations are done in discrete steps. In every time-step the position of each block is updated, new friction forces are generated if the block changed its position in the former time-step, and the total force acting on each block is calculated. Finally the corresponding displacement is determined for every car.

Before accepting the new values for the displacement is necessary to check, if this values fulfill our demands:

- they have to be positive (the cars can move only ahead), otherwise we leave the coordinate unchanged
- the distance between two blocks cannot be smaller than a $d_{\min}$ value (drivers have to keep a minimum distance from the car ahead, otherwise the distance will be considered $d_{\min} = 0.3$)
- the drivers have to respect a speed limit, so the displacement in one time-step cannot exceed $d_{\max}$. In the simulation the limiting value was choosen at: $d_{\max} = 1$.

After updating the position of each block, $j \in \{1, 2, 3, \ldots N\}$, respecting the rules formulated above, and collecting the relevant data for the dynamics of the system, the time is updated: $t \to t + 1$, and the simulation goes on updating first the friction forces, if necesary, and so on.

A part of the parameters were fixed at the start of the simulation, so only three free parameters remained: the number of cars, N, the step of the first car, d_0, and the disorder level in the static friction, σ. By choosing different values for the free parameters, it is important to find out, how these parameters affect the relevant quantities of the system. Quantities characterising the whole system and quantities that are important for one component were studied, too.

First the $P_>(s)$ cumulative stop-time distribution (probability that a car has longer resting time than a given s value) was investigated for various cars in a chain. For a given car in the row the cumulative distribution function becomes a logarithmic one. This means that in the limit of large s values for the car in the critical position -and for all cars behind it- the $g(s)$ stop-time distribution function is a C/x power-law type (Figure 11).

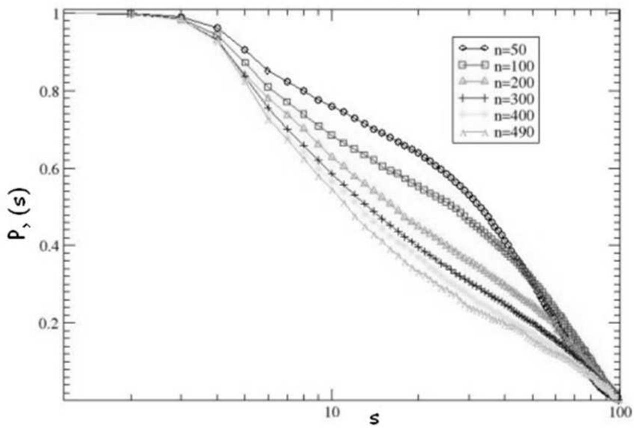

Figure 11. Cumulative stop-time distribution functions for various n car positions on normal-log scale ($N = 500$ vehicles, drag velocity fixed at $\nu = d_0 = 0.3$ and dissorder in the static friction σ=2).

As a second step the car in the position n=300 was chosen. The cumulative stop-time distribution was plotted for fixed disorder level and different drag-step sizes and for a fixed drag-step value, as a function of the s fluctuation of driving attitudes. Our conclusion was, that for fixed disorder level there is a critical value of drag step (drag velocity), for which the distribution function will become a C/x type power-law. So, there is a worst "drag velocity" for which the car in pozition n will be in a critical state, characterized by largely fluctuating stop-times. For a fixed drag-step we obtained a critical disorder value ($\sigma \approx 1.7$), for which the car has a logaritmic cumulative stop-time distribution, thus a power-law type distribution for the stop-times $g(s) = C/x$. This is a phase-transition-like behaviour, similar with the one obtained for the spring-block model applied to model Barkausen noise. Since this phase transition is induced by disorder, we call it disorder-induced phase-transition.

The study presented above was made in year 2009, and was only the first step in applying the spring-block model for modeling highway traffic. The newer study made by F. Járai-Szabó at al. [26] is more accurate and detailed and in parts confirms our most important conclusion: for every car in the row there is a critical disorder level where the state of a car is critical. A disorder induced phase transition is present as a function of the disorder in driving attitudes. For small disorder levels the stops are uncorrelated and no collective behavior is present. For higher disorder values correlated stops emerge and collective behavior arise.

In conclusion the simple mechanical spring-block model can be adapted with success for modelling the single-lane traffic. Of course, highway traffic could be modelled using other tools as well (agent-based models, or fluidum dynamics), but this example shows, that sometimes a large diversity of complex and quite different phenomena could be handled using very simple, pedagogical models.

The network approach to complex systems

Networks are the backbone (skeleton) of complex systems, so network view is very useful in investigating complex systems. Network models give a visual representation of the relevant interaction topology and the hierarchy (the importance) of the constitutive elements, offer precious information about the dynamical laws governing the time-like evolution of the system and allow a statistical description of the whole, even if we have partial knowledge about it [27].

Here we present and analyze a real network, the Erasmus Student Mobility network. For the year 2003 it contains 2333 universities and 134330 students (who travelled from a university to another in this project). This system has as nodes the universities, and the student exchanges are the links.

The analysis was made not in the idea of exploiting the program itself, but in order to investigate this complex real network, to describe it using mathematical tools, to construct some computer models of it and finally to evaluate the quality of the constructed models comparing it with the corresponding values calculated from the real dataset.

The ESM database we had was a huge one, so when making a graphical representation we had to skip over a part of it. In the case of the weighted ESM graph we could represent the universities having exchanged at least 15 students, (Figure 12), or we could choose to represent the hubs of our non-weighted graph (universities having at least 55 links, as Figure 13 shows).

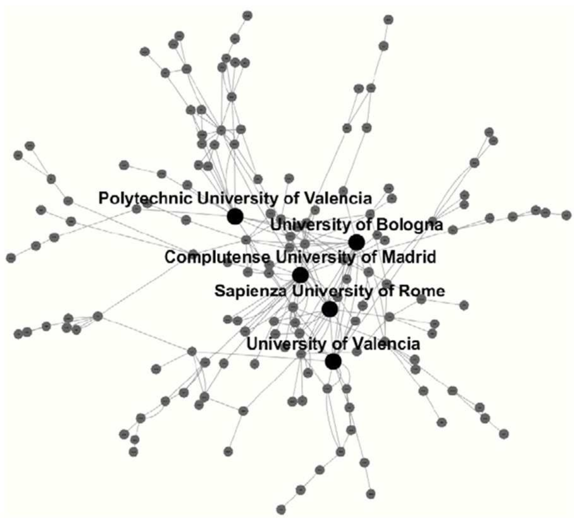

Figure 12. Part of the weighted ESM network (including 149 universities with at least 15 exchanges in the year 2003) [28].

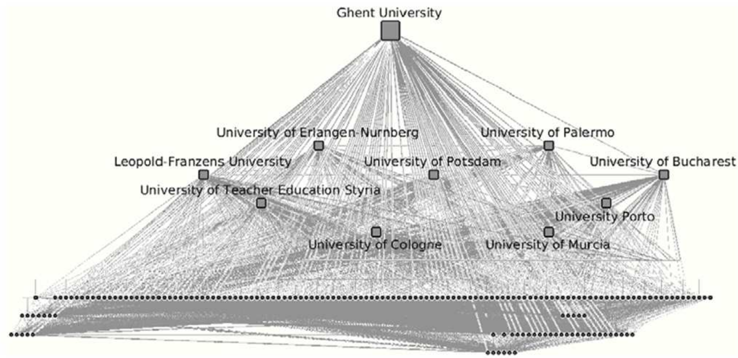

Figure 13. Part of the non-directed and non-weighted ESM network (containing the elements with at least 55 links, in a hierarchical representation) [28].

The presence of these hubs on both graphical representations suggests a complex network. Our expectation was to obtain a power-law degree distribution, high clustering coefficient, small average distance and preferential linking.

First the non-directed, non-weighted network was analyzed (the network of professional connections between universities). The network -due to our expectations- proved to be a strongly connected one. Its global clustering coefficient was 0.183, the local clustering coefficient 0.292, and there is a short average distance between the nodes 2.91, as we have expected. Surprisingly, no preferential linking could be revealed, and instead of power-law degree distribution our ESM network showed an exponential one.

On Figure 14 the $r(k)$ degree-rank function is represented. Since our data fits a strait line on semi-logarithmical axes, we have to conclude, that this complex network is not scale-free, as we have expected: the degree-rank function is exponential, so the degree distribution has also the same shape. This result can be explained using the maximum entropy principle.

Another feature of the complex social networks is their preferential linking or assortative mixing. First the degree of neighbour-nodes and then the local clustering coefficients of the nodes were plotted as a function of the degree of nodes. Results suggested no preferential linking in our non-directed and non-weighted ESM network.

A successful model for our non-weighted and non-directed ESM network-like graph can be made using the simple configuration model. After constructing the model network we compared it with the real ESM network. For the global clustering coefficient, average local clustering coefficient and average distance between two nodes (largest component) the values for the real ESM and the model network were close to each other, so we concluded, that our model obtained with the simple configuration method with random link-allocation describes well our real network, so it can be used for further study.

An exchange is, usually, unidirectional. One student goes OUT from one university and enters IN another. This means, that our network can be treated as a directed network,

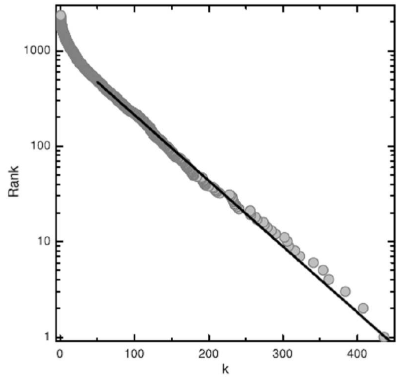

Figure 14. Rank-degree plot (on semi-log axes) for the non-directed ESM network. The highly connected universities (universities with more than 50 connections) are represented by filled circles, and the thick continuous line is the exponential which fits these data [28].

too: there is a possibility to consider the ESM graph formed only by IN or only by OUT connections.

Analyzing the database of the real ESM network it can be seen, that 2/3 of its connections are unidirectional ones (only IN or OUT connection), and 1/3 of them is bidirectional. The links of the nondirected and non-weighted model network were considered bidirectional with a 2/3 probability, and they got a random direction with 1/3 probability. The resulting model network was compared to the real network by plotting the rank of the universities as a function of the IN and OUT connections they have.

The results on Figure 15 showed that the model is similar with the real network: The values for the directed real network and for the directed random graph are very close to each other.

If we are interested in the structure and strength of existing connections, we have to consider the ESM network as a weighted graph (The strength or weight assigned to a connection is given by the number of students realizing it.) First the students participating in the project had to be partitioned on their "home" universities. Leaving a university is likely to be linked with the number of OUT links the university has, so using the real database the number of leaving (SOUT) students was plotted as a function of the (kOUT) OUT connections of that university. The result on log-log axes suggested a power-law, scaling with exponent 1.17 Using this correlation the students were distributed on their "home" universities, so finally every node of our model network had a number of OUT links, and a (bigger or equal) number of students assigned.

Now every OUT link had to be populated by students: this could be done randomly in an uncorrelated manner, or preferential, too. The construction of the model network was made in both ways, and results were compared with the real network. On Figure 16 the

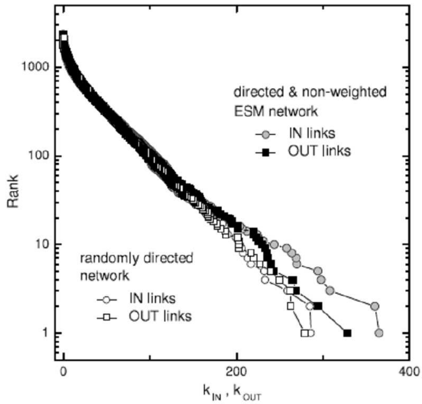

Figure 15. Rank of universities as a function of their IN or OUT degree for the directed and non-weighted ESM network (filled symbols), and for the randomly directed model network (empty symbols).

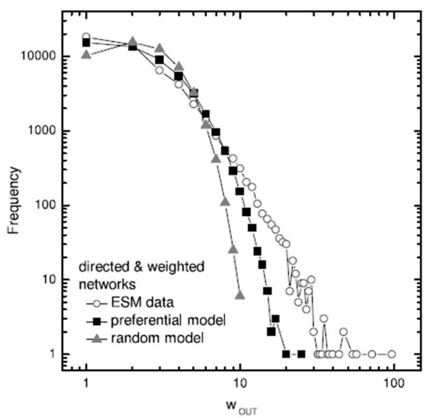

Figure 16. Comparison of weight distributions for the directed and weighted networks: ESM network (open circles), the directed version of the network obtained by the configuration model with random (filled triangles) and preferential (filled squares) generation of weights.

weight-distribution of nodes was plotted for the real weighted and directed ESM network (empty circles), and for both of the model networks: for the one obtained with preferential connection (filled squares) and for the one obtained with random connection (filled triangles), too. As it can be seen, the model network obtained with preferential linking describes much better our real ESM network, than the model constructed with random weight allocation. This means, that in the directed and weighted network preferential linking is present.

In this chapter we considered and studied by means of statistical physics methods a large-scale complex network. This study can convince us, that the network view is suitable when approaching complex systems. Network studies and network models can offer precious information about the dynamical laws governing the time-like evolution of a complex system.

We hope that the presented examples convinced the reader about the importance of choosing the right model for exploring collective phenomena. Briefly, since "collective phenomena" is a concept covering a very broad field, a broad variety of models could be used in the investigation of these processes. These models are tools at the disposition of the researcher: his art consists in choosing the proper tool and using it properly.

Conclusions

During the 20^{th} century mankind has experienced a booming development, and -accordingly-the new limits of its possibilities, too. Totally automaton production lines can do routine jobs of man, only programming and supervision is needed; wired and wireless networks provide us energy, information and travelling possibilities; fuel, electricity, the internet or traffic-networks are all huge and amazing but have proven to be vulnerable, too. Any failure of one screw, belt or bearing causes the failure of the whole production line, or an unexpected event taking place at an important node of a network could cripple it for a while. In order to restart it intervention is needed: it would not simply "heal itself" as living organisms do...

Given all our sophisticated equipments and machines, we have to recognize, that natural systems having big number of simple components are much more reliable and fault-tolerant: they can "feel" their environment much better, they can react to environmental changes much faster, they can recover, heal themselves in no time and are even capable to organize themselves (without any centralized control).

As a matter of fact, we have to admit that nature is perfect. So being in the possession of all the knowledge and technical facilities man of the 21^{ts} century is seeking, again, for the mechanisms which make it so perfect. Top researchers in robotics work to implement ingenious solutions provided by nature for improving robustness, reliability and self-adjusting properties of their products. Their aim is not the construction of big and sophisticated machines equipped with different sensors, controlled and commanded by a central computer. The era of human-like robots with two red eyes remains the protagonist of cartoons.

The new generation-robot would rather be a system of small and simple entities interacting with each other and with their environment, performing their tasks based on the principle of collective behaviour. Lifting a heavy piece is not necessarily done by a hoisting crane: swarm-robots can do the job as well (just like ants do). The idea of using the concepts and mechanisms of collective behaviour in order to develop biological inspired techniques is brilliant, but implementing it demands not only knowledge and technical facilities: Man‘s vision about production systems has to be reconfigured, too. Hierarchical arrangement and central coordination gives place to cooperation, responsiveness, self-reconfiguring, and self-assembling properties of the components. In fact all these concepts have their origins in collective behaviour [29].

Briefly, collective behaviour is a brand new field of study and a source of inspiration, since it gives an insight in the mysteries of our marvelous world and gives us a key to revolutionary solutions for yet unsolved practical and technical tasks.

Selected bibliography

1. J. Ginneken, *Collective behavior and public opinion. Rapid shifts in Opinion and Communication* (Lawrence Erlbau Associates, New Jersey, 2003)

2. L. C. Warren, *Two views of dissolution: an examination of collective behavior theory and critical theory on the subject of mass social behavior*, Ph.D. thesis, University Simon Fraser, Burnaby, Canada (1976)

3. E. Káptalan, L. Szabó, C. Szász, Z. Néda, "Collective Behavior - A General Survey", in *Journal of Computer Science and Control Systems*, vol. 4(1), pp. 53–60 (2011)

4. I. D. Couzin, J. Krause, "Self-organization and collective behaviour in vertebrates", in *Advances in the Study of Behaviour*, vol. 32, pp. 1–75 (2003)

5. D. J. T. Sumpter, "The principle of collective animal behaviour", in *Philosophical Transactrions of The Royal Society B*, vol. 361(2), pp. 5–22 (2006)

6. E. Bonabeau, G. Theraulaz, "Swarm Smarts (behaviour of social insects as model for complex systems)", in *Scientific American*, (March), pp. 72–79 (2000)

7. S. Camazine, "Patterns in nature", in *Natural History*, vol. 112(5), pp. 34–41 (2003)

8. I. S. Aranson, L. S. Tsimring, "Patterns and collective behavior in granular media: Theoretical concepts", in *Reviews of Modern Physics*, vol. 78(April-June), pp. 641–692 (2006)

9. C. Castellano, S. Fortunato, V. Loreto, "Statistical physics of social dynamics", in *Reviews of modern physics*, vol. 81(2/ april-june 2009), pp. 591–646 (2009)

10. S. Strogatz, I. Stewart, "Coupled oscillators and biological synchronization", in *Scientific American*, (December), pp. 102–109 (1993)

11. S. Strogatz, *Sync. The emerging science of spontaneous order* (Penguin Books, London, 2004)

12. Y. Kuramoto, J. Nishikawa, "Statistical macrodynamics of large dynamical systems", in *J. Stat. Phys*, vol. 49, pp. 569–605 (1987)

13. R. Mirollo, S. Strogatz, "Synchronization of pulse-coupled biological oscillators", in *Journal on applied mathematics*, vol. 50, pp. 1645–1662 (1990)

14. Z. Néda, A. Nikitin, T. Vicsek, “Synchronization of two-mode stochastic oscillators: a new model for rhythmic applause and much more”, in *Physica A*, vol. 321, pp. 238–247 (2003)

15. Z. Néda, E. Ravasz, Y. Brechet, T. Vicsek, A. L. Barabási, “Physics of rhythmic applause”, in *Phys Rev. E*, vol. 61, pp. 6987–6992 (2000)

16. R. Sumi, Z. Néda, “Synchronization of multimode pulse coupled Stochastical Oscillators”, in *Journal of optoelectronic and advanced Materials*, vol. 10(9), pp. 2455–2460 (2008)

17. G. Máté, E. A. Horváth, **E. Káptalan**, A. Tunyagi, Z. Néda, T. Roska, “Periodicity enhancement of two-mode stochastic oscillators in a CNN Type architecture”, in *IEEE Proceedings of the 2010 12th International Workshop on Cellular Nanoscale Networks and Their Applications (CNNA)*, vol. 5430275(IEEE Catalog Number: CFP10CNN-ART) (2010)

18. **E. Káptalan**, Z. Sárközi, A. Tunyagi, S. Boda, Z. Néda, “Synchronization of flashing electronic oscillators”, in *Joint Conference Third International Workshop of Nonlinear Dynamics and Synchronization and Sixteenth International Symposium on Theoretical Electrical Engineering*, 1569423423

19. S. Horvát, E. Horváth, G. Máté, **E. Káptalan**, Z. Néda, “Unexpected synchronization”, in *Journal of Physics, Conference Series*, vol. 182(012026) (2009)

20. **E. Káptalan**, Z. Sárközi, Z. Néda, S. Boda, A. Tunyagi, “Optimization induced collective behaviour in a system of flashing oscillators”, in *International Journal of Bifurcation and Chaos* (2011)

21. Z. Néda, K. T. Leung, L. Józsa, M. Ravasz, “Spiral cracks in drying precipitates”, in *Physical Review Letters*, vol. 88 (2002)

22. N. Chakrapani, B. Wei, A. Carrillo, P. M. Ajayan, R. S. Kane, “Capillarity-driven assembly of two-dimensional cellular carbon nanotube foams”, in *Proceedings of the National Academy of Sciences of the United States of America (PNAS)*, vol. 101(12), pp. 4009–4012 (2004)

23. K. Kovács, Z. Néda, “Disorder-driven phase tranzition in a spring-block type magnetization model”, in *Phys Lett A*, vol. 361, pp. 18–23 (2007)

24. Z. Néda, F. Járai-Szabó, **E. Káptalan**, R. Mahnke, “Spring-block models and highway traffic”, in *Control Engineering and Applied Informatics*, vol. 11(4), pp. 3–10 (2009)

25. Z. Néda, F. Járai-Szabó, **E. Káptalan**, “Spring-block models for complex phenomena - proceedings of CSCS 17, (17th International Conference on Control Systems and Computer Science), IAFA 10”, in , vol. 3, pp. 78–81 (2009)

26. F. Járai-Szabó, B. Sándor, Z. Néda, “Spring-block model for a single-lane highway traffic”, in *Central European Journal of Physics*, vol. 9(4), pp. 1002–1009 (2011)

27. A. L. Barabási, *Behálózva* (Pallas-Akadémia Kiadó, Csikszereda, 2008)

28. A. Derzsi, N. Derzsi, **E. Káptalan**, Z. Néda, "Topology of the Erasmus student mobility network", in *Physica A*, vol. 390, pp. 2601–2610 (2011)

29. L. Szabó, **E. Káptalan**, C. Szász, "Applications of collective behaviour concepts in flexible manufacturing systems", in *Journal of Computer Science and Control Systems*, vol. 4(1), pp. 187–192 (2011)

Published papers

ISI publications

1. Sz. Horvát, E. Á. Horváth, G. Máté, **E. Káptalan**, Z. Néda, "Unexpected synchronization", *Journal of Physics*, Conference Series, vol. 182, 012026 (2009)

2. Zs. Sárközi, **E. Káptalan**, Z. Néda, Sz. Boda, A. Tunyagi, T. Roska, "Optimization induced collective behaviour in a system of flashing oscillators", *International Journal of Bifurcation and Chaos* IJBC–D–00328R1.

3. Z. Néda, F. Járai-Szabó, **E. Káptalan**, R. Mahnke, "Spring-block models and highway traffic", *Journal of Control Engineering and Applied Informatics*, vol. 11, no. 4, pp. 3–10, (2009)

4. A. Derzsi, N. Derzsi, **E. Káptalan**, Z. Néda, "Topology of the Erasmus student mobility network", *Physica A*, 390, pp. 2601–2610 (2011)

Other publications

5. G. Máté, E. Á. Horváth, **E. Káptalan**, A. Tunyagi, Z. Néda, T. Roska, "Periodicity Enhancement of Two-Mode Stochastic Oscillators in a CNN Type architecture", in *IEEE Proceedings of the 2010 12th International Workshop on Cellular Nanoscale Networks and Their Applications (CNNA)*, 5430275 (2010) (IEEE Catalog Number: CFP10CNN–ART, ISBN 978–1–4244–6680–1)

6. Z. Néda, **E. Káptalan**, "A sokaság ritmusa", *Fizikai Szemle*, vol. 9, pp. 301–305 (2009)

7. L. Szabó, **E. Káptalan**, Cs. Szász, "Applications of Collective Behavior Concepts in Flexible Manufacturing Systems", *Journal of Computer Science and Control Systems*, vol. 4, no. 1, pp. 187–192 (2011) ISSN: 1844–6043.

8. **E. Káptalan**, L. Szabó, Cs. Szász, Z. Néda, "Collective Behavior - A General Survey", *Journal of Computer Science and Control Systems*, vol. 4, no. 1, pp. 53–60 (2011) ISSN: 1844–6043.

Conference participations and proceedings

9. Z. Néda, B. Molnár, V. Melinda, **E. Káptalan**, "Correlation clustering at the thermodynamic limit", invited talk at Yalta Optimization Conference 2010, Aug. 2-4, and submitted to Optimization Letters

10. **E. Káptalan**, Zs. Sárközi, A. Tunyagi, Sz. Boda, Z. Néda, "Synchronization of Flashing Electronic Oscillators", accepted in the proceeding Joint Conference Third International Workshop of Nonlinear Dynamics and Synchronization and Sixteenth International Symposium on Theoretical Electrical Engineering, Klagenfurt Austria, 2011, 1569423423, proceedings

11. Z. Néda, F. Járai-Szabó, **E. Káptalan**, "Spring-block models for complex phenomena", proceedings of CSCS 17, (17th International Conference on Control Systems and Computer Science), IAFA 10, vol. 3, pp. 78–81 (2009)

12. Z. Néda, **E. Káptalan**, "A nem várt ritmus, Fizikatanítás tartalmasan és érdekesen", Magyarul Tanító Fizikatanárok Nemzetközi Konferenciája, 2009 aug, pp. 269–274, ISBN 978–963241150–2