

## Chapter 2

# Towards Wave-like Approach

This chapter discusses some insights about fundamental properties of information rich social systems. It mainly focuses on (i) claiming general properties of information-based social systems, (ii) ways to model emergent and self-organizing features of social networks, (iii) discussion how to simulate complex social systems using field-based approach and multi-agent platforms. Additionally, chapter provides some ideas how to construct field-based communication network of intelligent agent's using currently available computational intelligence methods. A vision of new simulation paradigm offers some useful concepts to transform multidimensional factor space (representing a multiplicity of phenomenal forms and interactions) into the most universal spectral coding system. The chapter gives some ideas and examples how not only the communication mechanism but also the social agents can be simulated as oscillating processes.

### 2.1 Overview

Notwithstanding the appealing empirical power of the applied methods, modern social research is still fragmented with a lack of cohesive modeling media for understanding and simulating the highly complex nature of social behavior. Nevertheless, our understanding of the traditional economic systems is transforming. For instance, economists and financial specialists have started to doubt about common financial capital theories after several unpredicted financial crises took place during the last decade, e.g., Asia crises, Russia crises, LTCM fund crackup, ENRON financial group crash and the recent global financial meltdown, which has started from mortgage crises in 2007—just to mention a few. The world's largest institutional investors, for example commercial banks, insurance companies, retirement funds, and so on are focused on the development of new concepts.

Interdisciplinary research groups in Santa Fe Institute, MIT, Cambridge, Princeton, Stanford, Yale, Harvard, etc., are increasingly open for the use of

nonlinear, dynamic, and heuristically oriented techniques for the purposes of delivering new concepts, which can deal with simulation of nonlinear dynamics, unexpected price shifts, economic crises, transitional effects, etc. (McCauley 2004). However, constructed models mostly fail to describe such an evolving complexity as they (i) do not have the same order of complexity (or degrees of freedom) and (ii) do not evolve together with the object of investigation.

Today, we appreciate that critical social phenomena, pattern formation, bifurcations, and deterministic chaos occur in both inanimate and animate nature and are implicated in fundamental ways with evolutionary population dynamics and self-organization in biological as well as social development. One of the most widely applicable lessons from other disciplines is that when systems consist of competing elementary forces the tensions that arise create structural complexity. The emergence of complexity, an apparently common phenomenon, and the parallels between the architecture of physical, biological, and social systems only hint at the beginning of a synthetic theory that describes how evolution generates structure. In this book we imply that the employment of the proposed approaches should reveal (i) conditions for appearance of periodic and nonperiodic social cycles, (ii) conditions and features of population and information clustering, (iii) structural invariants of the social evolution.

Much research is concerned with the appropriateness of traditional research approaches and methodologies in the social research domain. There is a growing suspicion that the main hindrances are hidden in modern social processes, which are badly modeled using traditional top-down approaches. With the advent of the new information society, we are increasingly dealing with some modern social phenomena like the network economy, globalization, e-commerce, nonequilibrium dynamics, complex social emergence, predominance of intangible (informational) goods, generative micro-macro relations, etc.

However, there is fast growing empirical literature on multi-agent systems (MAS), which are used to model social phenomena from the bottom-up, like agent-based hybrid intelligent systems (Zhang and Zhang 2004), agent-based computational modeling (Billari 2006; Darley and Outkin 2007), agent-based simulation from modeling to real-world applications, generative social science (Epstein 2006), agent-based computational economics (Tsfatsion and Judd 2006) etc.

Notwithstanding some advances in the use of multi-agent systems, promises were not fully realized for a number of reasons, as it is a truism in the field that the key problems are hiding not only in the agents themselves, but also in the way they communicate, interact and interpret behavioral information available in social markets. This adds a whole new layer of complexity as we see it in the most complex real social networks today (e.g., financial markets) (Hoffmann et al. 2007).

These are highly heterogeneous information networks with many links and complex interrelations. Uncoupled and indirect interactions among agents require the capability of affecting and perceiving broadcasted information context. In this sense, we propose to model the information network as a pervasive information field (PIF). Such an approach gives appropriate means to enforce indirect and uncoupled (contextual) interactions among agents. It is expressive enough to

represent contextual broadcasted information in a form locally accessible and immediately usable by network agents.

One of the closest examples in this area is amorphous computing (Nagpal and Mamei 2004). Another interesting proposal in that direction is the multilayered multi-agent situated system (MMASS), which defines a formal and computational framework relying on a layered environmental abstraction (De Paoli and Vizzari 2003). MMASS was related to the simulation of artificial societies and social phenomena for which the physical layers of the environment were also virtual spatial abstractions. In the last decade, a number of other field-based approaches have been introduced, like gradient routing (GRAD), directed diffusion, “Co-Fields” at TOTA programming model, CONRO, etc. (Mamei and Zambonelli 2006).

In fact, almost all proposed systems are either employed for various technological or robotic applications and very few of them like MMASS, agent-based computational demography (ABCD) or agent-based computational economics (ACE Trading World application: the simulation of economic phenomena as complex dynamic systems using large numbers of economic agents involved in distributed local interactions (Tefatsion and Judd 2006)) are suitable for programmable simulations of social phenomena.

The study of coordinated models goes beyond computer science in that evolutionary computation, behavioral sciences, social sciences, business management, artificial intelligence and logistics also somewhat strictly deal with how social agents can properly coordinate with each other and emerge as globally coherent behaviors from local interactions. The major question we address in this study is: what is the natural and most efficient way of simulating complex information networking and interaction mechanisms in order to reflect the observed multiplicity of modern broadcasting telecommunication systems used by social agents?

To the author’s knowledge, the close match to the proposed idea is explored by Mamei and Zambonelli in their study “Field-based coordination for pervasive multi-agent systems” (Mamei and Zambonelli 2006). They have been trying to achieve coordination for multi-robotic applications by means of the field-based (analog of PIF) approach. This is an example of how engineers are starting to understand that, to construct self-organizing and adaptive systems, it may be more appropriate to focus on the engineering of proper interaction mechanisms for components of the system rather than on the engineering of their overall system architecture.

As a matter of fact, effective communication stands among the top most important issues in MAS (multi-agent systems) implementations (Billari 2006). Contractual-based handshaking between two agents shapes peer-to-peer communication in today’s MAS systems. Peer-to-peer communication occurs when (1) the connection between sender and receiver is bonded in time and space, (2) two agents exchange ontologically classified semantic information by using a common communication protocol or a matchmaking agent. This approach works well for simple networks. This is not so effective in the complex social networks where the agents’ direct and coupled “peer-to-peer” communication model is pushed aside by other noncoupled, indirect, or contextual communication mechanisms.

One obvious example can be seen in modern telecommunication networks, where peer-to-peer connection protocols are no longer prevalent. This happens mainly because they are not efficient enough for multitasking, parallel processing, congested traffic control, conflict resolution, etc., (Panko and Panko 2010).

Not accidentally, there is a striking structural similarity between modern telecommunications and social networks. In fact, the main information traffic in social networks flows through telecommunications networks, which act as a backbone of the modern network-based information economy.

In fact, the information era has shaped efficient protocols for complex information traffic in the telecommunication networks, where (i) each agent can instantly send and receive information simultaneously through multiple communications channels, (ii) information flows are locally managed by the agent's preferences as if having the ability to "tune" to different broadcasting channels, (iii) agents became processing, storing, and retransmitting nodes in the social networks (Nagpal and Mamei 2004). Information is spreading through a multitude of multimedia networks with the speed of light. After all, it does seem like we are immersed in emanating fields of virtual information. The intriguing conceptual question we want to raise for discussion below is whether there is an acceptable way of simulating complex social network phenomena using universal spectral frequency representation.

Hence, this chapter is organized as follows. After formulating major claims and assumptions about fundamental properties of self-organized systems in social domain, we give an example of some fundamental physical models, which can help to model such systems. Next, we elaborate about PIF approach, which gives some clues and basic design ideas for understanding how field-like communication mechanism can be implemented.<sup>1</sup> Afterwards, we discuss wavelike interaction mechanism between heterogeneous agents. Finally, we summarize the conceptual findings and offer future directions for related research.

## 2.2 Evolving Economic Systems

Following the analogy of telecommunication systems, we assume that the same principles of reductionism and universality should be applied to simulating platforms in the social domain, too. In other words, communication by agents should operate not in the (peer-to-peer) vector-based multidimensional semantic space, but rather directly in the form of multimodal energy (spectra) emanated and absorbed over the social network. The flow of energy (and associated with it, information) in the form of stylized fields, however, requires a somewhat different understanding of the agent's role and their interaction mechanism.

---

<sup>1</sup>On the other hand, in this chapter presented approach is not the only one in this book. In the next chapters, there are presented some other simulation ways too.

In essence, information plays a major role in the economic systems. Information and entropy are the most general estimators of complexity. Admittedly, information does not immediately depend on the physical units and quantities of the chosen reference system, but on the relative frequency of the event occurring in the observed system. We more and more tend to look at information as the third basic quantity beside matter and energy because of central importance of information.<sup>2</sup> In fact, energy is also a quantity similar to information as it has ability to be transported and stored in several physical quantities.

In economics, a new and interesting phenomenon arises if we acknowledge observation that capital is becoming an intangible good. In fact, capital (we assume it as accumulated potential energy) gradually takes form of information in the modern information societies. It means that developed economies have started to capitalize on pure intangible goods or services (Ormerod 1997). In this regard, we can imply that emerging complexity of social networks is gaining ground not in the Newtonian mechanics (statistically described for economic agents as some sort of physical interacting particles), but rather in the form of self-organized information with virtual fields, potential energy states, wave-like interaction mechanisms, etc. Following the above discussion, we can further imply that the modern social order pertains to information fields, ranging from organization of individual agents to the information markets.

In order to proceed further, first we have to name in systemic manner some basic OSIMAS assumptions about underlying principles, which may govern complex information societies. Below we will get to the basic universal laws and starting from there to proceed with some new conceptual proposes.

**1 Claim** *Effective attempts to simulate and model social behavior most likely pertain to artificially constructed self-organized systems.*

Such systems in depth and spread (comparing with original ones) can evolve in the virtual world settings. Successful imitation depends upon model setup, i.e., its emerging and self-organizing properties.

**2 Claim** *Modern information-based economic systems (e.g. financial capital markets) and social networks are mostly related with self-organized information.*

For instance, electronic currency and stock exchange (SE) markets deal exclusively with information content. Even more, in some SE electronic markets majority of market deals is made by the sophisticated algorithmic traders. This tendency is expanding exponentially to other electronic markets too. Similarly, social networks pertain to the self-organized information too.

**3 Claim** *In terms of modeling, the closest fundamental match for the complex self-organized information is energy, which can be stored, transformed and distributed.*

Information being dimensionless expresses itself in a plenty of different forms as its carriers (Arndt 2012). The closest fundamental match for information in terms of

---

<sup>2</sup>The same as energy, information is a quantity that depends on the choice of the system of reference. It can be specified only with the respect to the reference system.

properties is energy. It can and should be employed for modeling self-organized information properties.<sup>3</sup>

**4 Claim** *In contrast but not in contradiction to the fundamental second law of thermodynamics there are living organisms and their societies, which in the process of self-organization are creating organized structures (negentropy) in expense of increasing entropy in the surrounding environment.<sup>4</sup> In the process of self-organization is produced new information, e.g., new structures or behavioral patterns.*

In the open system, it decreases entropy (disorder) inside the system, but increases chaos outside the system. In this sense, the second law of thermodynamics holds.<sup>5</sup> Emergent structures are maintaining disequilibrium between inner order and outside chaos.

**5 Claim** *Living beings containing self-organized information are usually not stable because they are exposed to the opposing fundamental processes of entropy (loss of order) and self-organization (creation and maintenance of order).*

In general terms there are at play two universal processes: one for self-organization of information and another for disorganization (entropy governed by the second law of thermodynamics). Both processes interact with each other creating a complex flux of changes.

**6 Claim** *Information society pertains to a new type of economics where wealth is capitalized in a form of intellectual, commercial and technological information. It is stored in various information markets and has capacity of spreading globally through nets of information channels with the speed of light.*

Modern information economy cannot be easily described by classical Adam Smith's approach as statistically aggregated mechanical approaches simply oversimplify the reality. In short, we are moving to the age of information economics. So, we have to look for fundamentally different modeling tools, which inherit the self-organized properties of economic agents and information society at large.

**7 Claim** *Modern information societies can be understood and modeled as accumulated potential fields of various information, where energy or excited states are*

---

<sup>3</sup>Information is an intensive quantity (energy is extensive), which means that summation of the two pieces of information leads to accumulated information that is less than or equal to the sum of the two pieces of information. The accumulated information is only equal to the sum of the single pieces of information when there is no mutual information between the subsystems (independence of the random variables).

<sup>4</sup>The second law of thermodynamics states that the entropy has to increase in the closed systems, which indicates that the disorder (disorganization) in closed systems has to increase.

<sup>5</sup>Self-organized systems are not closed systems. So, there is no contradiction with the second law of thermodynamics. There are, though, some limits concerning conservation of information analogous to the conservation of energy, as for example in the time–frequency measurements. This relation shows us that any gain of information that we obtain by smaller sample intervals in time leads to a loss of information of larger frequency intervals in the frequency domain. Obtaining information always means losing it, but in the different scale in time or frequency.

*propagated not only in a form of corpuscular kinetic interactions between economic agents, but increasingly more like information fields transmitted through the telecommunication systems or mass media channels.*

This gives a good reason to model world capital spatial and temporal dynamics through the means of interfering information waves oscillating in different frequencies, amplitudes, and phases via the geographically distributed population.

In summary, for the effective implementation of the wave-like modeling approach we can employ spectral representation as a universal energy-information warehouse. For that reason we first have to transform all tangible objects-resources into their energy equivalents and then interrelate different types of energy as intangible information stored in the form of corresponding sets of spectral bands. The reasoning behind this is based on the principle of reductionism and universality as we are looking for the means to reduce a multiplicity of forms into one representation.

Thus, according to the proposed approach, agents can be interpreted as processes, which exchange multimodal energy depending on the information they have. We assume that agents are rule-based, input-output reactive systems. Changing an agent's behavior means modifying its characteristic parameters in the behavioral rule set.

## 2.3 Methodological Framework

To begin with, the central critical question is how we could model the postindustrial (self-organized) information society, which can be characterized by (i) value creation using knowledge (the main capital resource), (ii) a net of various information channels, (iii) on-line processing, storage, and transmitting (OLAP) systems in a chain: data  $\rightarrow$  information  $\rightarrow$  knowledge. There are no easy answers. However, proceeding comments below may shed some new light.

Much research is concerned recently with an answer as to why economic systems behave chaotically. The understanding might rest on the perception that the ability of the system in chaotic motion to explore wide regions of its phase space, and thus utilize information about a large collection of potential states of the system, can have distinctive positive implications for what the economic system can do in achieving its required functions. Biological or social systems that do not take advantage of chaos in their state spaces may not be able to participate in evolution to the extent we understand that as adaptation to changing environments (Abarbanel 2012).

Social networks are complex systems with inherited chaotic behavior. It means we cannot construct effective long-term forecasting models. Instead, we should look for models which have the same chaotic properties (e.g., invariants) as the original systems (Peters 1996). Such models are not exclusively targeted only for better forecasting. They can target something not less important, i.e., simulation of the geometrical structure of the real data (mimicking chaotic invariants' values). Such approach stresses more on the simulation of complexity itself. In practical terms, it can give close enough estimates for, e.g., average number of peaks or minima via

given period, long-range dependencies, self-similarity estimates, major periodic and aperiodic cycles, expectations for critical events, etc.

Let's explore one example in a more formalized way. We are going to construct a physical model related not only with modeling of the set of real people in economic system, but also with a media of interaction transmission. We admit a set  $\forall E$  of economic agents as information emitting sources.

The analogous (simplest) physical model can be presented using energy carried by a stretchable string (Bronshtein et al. 2013), see Fig. 2.1a. Here we have just one physical dimension  $x$  and economic agents are lined up in it composing a string  $U$ . The string of agents lies in between the two stylized fields as shown in the Fig. 2.1a). When a perturbation is present, it pertains to potential and kinetic energy. However, perturbations originate not from the ends of the string (as it is usually implied in the physical string models), but from the both fields as it is represented in Fig. 2.1a)

$$dK = \frac{1}{2} \lambda_0 dx \left( \frac{\partial \eta}{\partial t} \right)^2, \quad K_1 = \frac{dK}{dx} = \frac{1}{2} \lambda_0 \left( \frac{\partial \eta}{\partial t} \right)^2, \quad (2.1)$$

where  $dK$  stands for kinetic energy of an element  $dx$  of the string ( $\{dx\} \rightarrow \{\{x\} | x \subset U\}$ );  $K_1$  stands for kinetic energy density and  $\lambda_0 dx$  is the mass of the element  $dx$ . Partial derivatives here denote the dynamics of perturbations.

For negligible Young modulus (i.e., for idealized string with perfect flexibility) the work done to stretch the string an amount  $\Delta s$  against a constant tension  $\tau_0$  is  $\tau_0 \Delta s$ , which therefore equals the gain in potential energy stored in the displaced string.<sup>6</sup> Hence the total potential energy  $V$  and local potential energy  $V_i$  for the agent  $i$  are

$$V = \frac{1}{2} \tau_0 \int_0^l \left( \frac{\partial \eta}{\partial x} \right)^2 dx, \quad V_i = \frac{1}{2} \tau_0 \left( \frac{\partial \eta}{\partial x} \right)^2, \quad (2.2)$$

where  $l$  stands for the length of the string.

The string model can be helpful realizing how oscillations can represent dynamics and propagation of vibrational states, without simultaneous mass transport. Systems in which waves arise may be envisaged as being composed of infinitely many mutually coupled oscillators (agents). Vibrational state of each individual oscillator depends on the states of neighbor oscillators (agents). (see Fig. 2.1a).<sup>7</sup> The energy of the whole system is constantly redistributed among the oscillators.

Next, let's to proceed with some physical model to deal with a key characteristics, i.e. entropy and information. For analogy, we can use a physical model based on the most basic laws of thermodynamics. First, let say we have a closed homogenous

<sup>6</sup> $\tau_0$  can be interpreted as permeability for conduction of transversal wave energy. In the broader sense, it can be a function of location and time  $\tau_0(x, t)$ .

<sup>7</sup>A quantity which describes the oscillation state is written in the form  $\omega t - \vec{k}\vec{r} + \phi$ .





**8 Claim** *There are no closed processes in nature where the total entropy decreases, but this is locally possible in the open self-organized subsystems, which contain information how to make work the above described “heating pump”. In this sense, self-organized living subsystems can be interpreted as entities capable to reduce inner entropy decreasing randomness of their vibrational states in expense of increased entropy in a whole environment.*

Oscillators inside the “Bubble” are self-organized, capable to sustain the inner order and membrane’s entropy (disorder) filtering properties subject to the information they have. The dynamics of interplay between self-organized and disorganized states takes place in the membrane itself. In this way, by input of work  $A$  ( $A < 0$  because work is done against prevailing opposite force from disorganized environment, see Fig. 2.1) membrane’s oscillators get equivalent, but opposite sign potential energy  $\Delta E_p^I > 0$ , see Fig. 2.1b.<sup>11</sup> At the same time moment it changes the information content in the system relative to environment as part of existing uncertainty  $S$  (entropy  $S > 0$ ) is decreased locally by  $\Delta S^{\text{bubble}} < 0$ . System (the “Bubble”) is freed from chaos, noise or more generally from uncertainty. It creates structured forms or complex arrangements increasing the information of the system. Sure, this process is far from trivial, because (i) in the closed system holds the second law of thermodynamics, (ii) every self-organized system has a property to split the flow of entropy into two opposite parts, i.e., entropy  $\Delta S_S$  and negentropy  $\Delta S_N$  [Brilloun-Schrodinger’s negentropy (Brillouin 1953)] balancing with residual  $\delta$  ( $\delta$ —the overall increase of entropy in the transition process as required by II thermodynamic law in the closed system) between them

$$\Delta S_S + \Delta S_N = \delta, \text{ where } \Delta S_N < 0, \Delta S_S > 0, \delta > 0. \quad (2.3)$$

Because of efficiency  $\eta = (\Delta S_S + \delta) / \Delta S_N < 1$ , the heating pump releases some additional irreversible heat  $\delta > 0$  (increasing total entropy, i.e., disorder). In this way, we may also imply that order develops from chaos in the self-organized living systems. However, self-organized structures are far from a state of equilibrium.

Hence, the law of energy conservation and II thermodynamic law give us

$$A + \Delta E_p^I + \Delta \kappa = 0, \quad A < 0, \Delta \kappa > 0, \Delta E_p^I > 0, \quad (2.4)$$

where changes of all energy and entropy for the closed system can be described<sup>12</sup>

$$\begin{cases} \Delta E = A + \Delta E_p^I = \Delta \kappa \\ \Delta S = \Delta S_S + \Delta S_N = \delta \end{cases}, \quad (2.5)$$

<sup>11</sup>Here holds energy conservation law. Superscript  $I$  in the  $\Delta E_p^I$  term indicates information origin for this potential energy.

<sup>12</sup>Note that, in the process of information gain, increases kinetic energy  $\Delta \kappa$  and closely related heat entropy  $\delta$  yielding to  $\Delta \kappa \simeq \delta$ .

where  $\Delta E$ —system’s total energy,  $\Delta S$ —increased entropy (heat) energy,  $\Delta \kappa$ —change of kinetic energy (see Eq. 2.1). Of note is that “Bubble’s” self-organized membrane does a job of selective filtering of noise (uncertainty or entropy).<sup>13</sup>

In fact, energy conservation law is not violated, because the whole system’s energy remains the same. Only some part of the inner heat (low order energy) is transferred locally from “Bubble’s” inside to the outside. As if self-organized “Bubble” is filtering out some frequencies of white spectrum making only some inner oscillations to take strength.

**9 Claim** *Gained information (order) in a form of increased negentropy comes in the expense of the increase of heat (entropy related disorder) outside the boundaries of self-organized system.*

In the utmost case, absolute negentropy (order) can be achieved by filtering all possible oscillations from a white spectrum leaving a system idle of any oscillations (the point in the center of “Bubble” with zero potential energy). Self-organized systems have learned how to use surrounding chaos by filtering its random oscillations in this way transforming their oscillation spectra. Properties of membranes play crucial part in the process as they are multidimensional, i.e. segregate different energy states, entropy, and information (as well as various organizational) states.

**10 Claim** *From another perspective, we can also imply that white spectrum has all possible set of oscillations for any type of orders giving birth to any type of model representations for self-organized entities. Increasing complexity of the self-organized systems in informational sense means climbing up on the ladder of potential energy and getting closer to the realm of chaos, where more and more sophisticated patterns of oscillations occur. It leads to self-organized systems with chaotic, nonlinear, highly adaptive, and unpredictable behavior.*

Purely for the modeling purposes we imply that each economic agent can be interpreted as a unique spectrum of oscillations. According to the chosen approach, self organized oscillations play crucial role in the dynamics of emerging complexity and chaos structures on the border between disorder and self-organization.

Let’s see how presented physical model can be related with the economic (financial) case. First, one can recall that continuous time economics always deals with time dependent relations as functions of time (in financial markets case we usually deal with stochastic dynamics). In every case, we have a set  $\exists F$  of functions  $\{f(t), p(x)\}$

$$F = \left\{ \begin{array}{l} f(t), p(x) \end{array} \middle| \begin{array}{l} f(t) \text{ time dependant functions describing properties of economic agents} \\ p(x) \text{ time independant parametric properties of economic agents} \end{array} \right\}. \quad (2.6)$$

---

<sup>13</sup>Unlike neo-classical economists, which assume the unphysical equivalent of a hypothetical economy made up of Maxwellian demonish like agents (who can systematically cheat the second law of thermodynamics), we do obey the fundamental laws here.

If the set of functions  $f(t)$  satisfy the Dirichlet conditions, i.e., (a) the defined interval can be decomposed into a finite number of intervals where the function  $f(t)$  is continuous and monotone, and (b) at every point of discontinuity of  $f(t)$  the values  $f(t + 0)$  and  $f(t - 0)$  are defined, then the Fourier series of this function are convergent. At the points where  $f(t)$  is continuous the sum is equal to  $f(t)$ , at the points of discontinuity the sum is equal to

$$(f(x - 0) + f(x + 0))/2.$$

Every function  $f(t)$ , satisfying the Dirichlet conditions, can be represented mathematically using Fourier series as a periodic function of period  $T$  (superposition of sine and cosine oscillations).

We can recall here that superposition of sine and cosine function is an oscillatory function itself. Arbitrary periodic phenomena may be represented as superposition of pure sine and cosine oscillations (Benenson et al. 2006). The result of Fourier analysis is represented by frequency–amplitude plot. We can use Fourier synthesis for construction of a complex time signal out of several sine and cosine functions of different frequencies and amplitudes.

In the case of nonperiodic functions on the interval  $(-\infty, \infty)$  Fourier series is replaced by the Fourier transform and inverse Fourier transform. In sum, there is a way  $\exists \Gamma$  to transform  $\forall F$  set of only time dependant functions  $\{f(t)\}$ , which describe the behavior of economic agent, to a set  $\exists \Psi$  of time–frequency dependant functions  $\xi(A, \omega, t)$  and vice versa

$$\Gamma : F \Leftrightarrow \Psi, \quad \forall F | \{f(t)\}; \exists \Psi | \{\xi(A, \omega, t)\}. \quad (2.7)$$

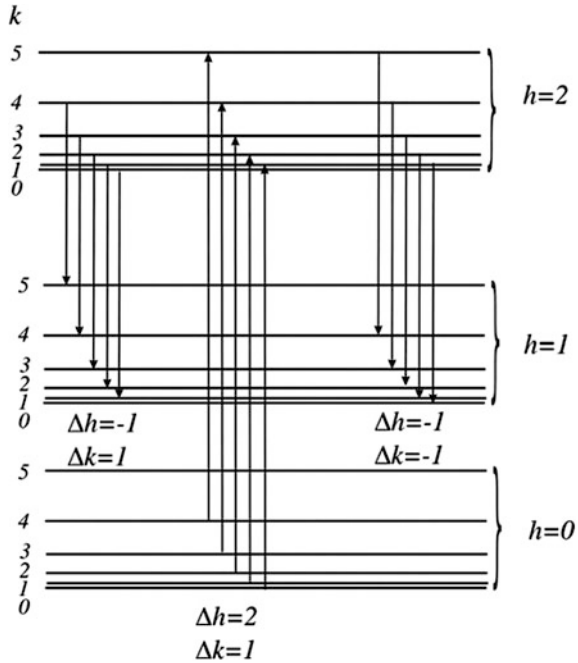
In conceptual terms, this is a very important inference as it shows that our dynamic social model can be simulated using frequency terms. For the effective implementation of the proposed oscillations-based approach each economic agent is interpreted further as a source of unique composition of oscillations. A set of such agents represents PIF (pervasive information field) model, i.e., superposition of waves and distribution of associated energy accordingly.

**11 Claim** *All time dependant state functions of economic agents' can be mapped into the frequency domain. In this way, an agent becomes represented in terms of a unique composition of oscillations (spectra).*

Instead of time dependant functions Fourier transform gives an opportunity to use spectra for the same modeling purpose. We may also mention some other transformations like Gabor and wavelet, which can be employed too (Benenson et al. 2006).

Our aim is to find out how spectra can interact and carry out the information, which is the universal attribute we have for measuring the basic properties of information societies. In general sense, the most universal measures of information are entropy and

**Fig. 2.2** The principle of quantization of energy-information states for social agents having an analogy to the rotational-vibrational states of diatomic molecular model (where  $k$ —the rotational quantum number and  $h$ —the vibrational quantum number)



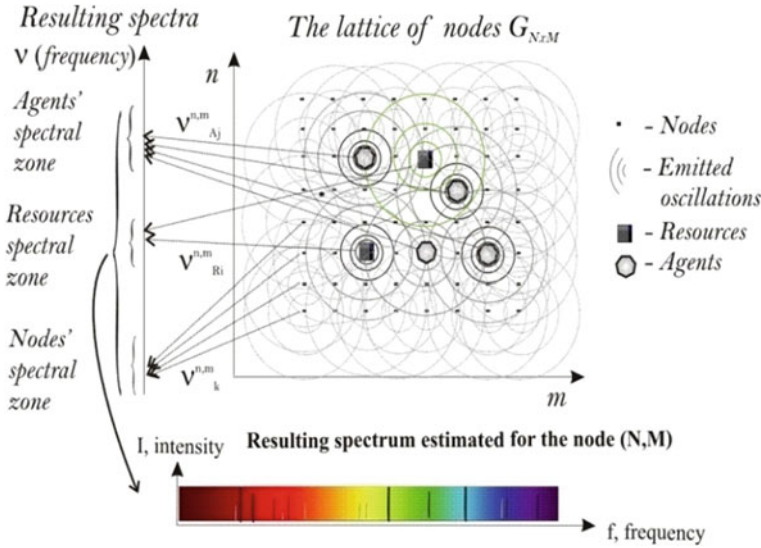
Brillouin-Schrodinger negentropy.<sup>14</sup> In the next section, we are going to see some hints for construction of PIF and wave-like interaction mechanism.

## 2.4 Pervasive Information Field (PIF) Concept

This section gives brief PIF outlines which are designed for (i) the construction of virtual media for information and resources (associated energy) exchange and (ii) the quantization of agents' internal states.

In a certain sense, we are proposing a universal energy-information state space model for the agents and their systems, see Fig. 2.2. All possible states are coded as

<sup>14</sup>Schrödinger gives the following example of the term elementary “negentropy” increase  $N = -S = k \log \frac{1}{D}$  (where  $D$ —number of macroscopic states system is available to adopt,  $1/D$ —probability to be in one certain state) for living self-organized systems: living organism lives on food, which merely supplies our body with negentropy (for compensation of the loss of negentropy by the degradation of energy, i.e. transformation to heat). The energy contained in this food is not the crucial factor, because the energy is conserved. It is the negentropy that is the crucial factor, because the decrease of entropy, enabled by this negentropy, leads to an increase of the grade of energy (see Thompson, Kelvin grades of energy) and this is the reason living organisms can create complex structures.



**Fig. 2.3** PIF composed from agents, resources and nodes, which all are represented (see on the left side) by corresponding spectral bands. An example of resulting spectrum lines for the node  $(N, M)$  is given below the upper chart

unique oscillations in the frequency spectra.<sup>15</sup> In our proposed state space model, an arbitrary number of possible states for a given economic system can be coded and decoded.<sup>16</sup> Afterwards, with such a universal coding system we can create a set of conditions and rules for transitions between different energy-information levels.

We need a couple of quantum numbers to describe an infinitely large pool of states and transitions between them. We should bear in mind, however, that transitions between different energy states carry not only energy, but also information about quantum states, e.g., combination of quantum numbers like  $h$  and  $k$  as it is depicted in Fig. 2.2, bear exact information about the particular state.<sup>17</sup>

In the proposed PIF approach, fields are operating on the rectangular lattice  $G_{N \times M}$  consisting from a set  $\Omega_{N,M}$  of virtual nodes (we assume that nodes are distributed evenly on the lattice). Size of the lattice  $N \times M$  is arbitrary. All resources  $\{R_i\}$  and agents  $\{A_j\}$  are distributed only on these nodes, see

Figure 2.3. Each particular node  $\Omega_{N,M}$  represents a point on virtual lattice space  $(n \in N, m \in M)$ , which functions are (1) for discrete time intervals to evaluate

<sup>15</sup>The agent's internal states are associated with possessed information, i.e. resources, behavioral patterns, internal parameters.

<sup>16</sup>Different agents can have concurrent oscillations (frequencies). It does not forbid an agent to have a unique set of own oscillations.

<sup>17</sup>Released or absorbed energy corresponds to the transitions between different energy levels.

incoming fields and produce corresponding spectra representations, (2) to oscillate at own fixed natural frequency  $v_{n,m}$  emanating it to the surrounding PIF.

In order to reduce computations, resulting spectra are evaluated only for nonempty nodes. Any node can be occupied either by agent from the set  $\{A_j\}$  or by resource from the set  $\{R_i\}$ . Each agent and resource has own natural oscillation frequency  $v_{n,m}^{A_j}$  and  $v_{n,m}^{R_i}$  correspondingly, see Fig. 2.3.

Field intensities are decreasing according to the  $D^{-2}$  or similar negative power law, where  $D$  represents distance from the emanating source measured in virtual space using relative units.<sup>18</sup>

We will only discuss some ideas about the formal approach below. The most relevant model for PIF is adapted from physics using harmonic oscillators, where energy quantum for elastic wave

$$E = \hbar \cdot v, \quad (2.8)$$

where  $\hbar$ —quantum of action.

In physics, this energy quantum is called phonon.<sup>19</sup> Then the energy states  $E_k$  of the harmonic oscillator are quantized using phonons

$$E_k = \hbar \cdot v \cdot (k + 1/2), \quad k = 0, 1, 2, 3, \dots, \quad (2.9)$$

where  $v$  stands as a base frequency. We may as well rewrite Eq. 2.9

$$E_k = \hbar \cdot (v \cdot k + v/2)$$

having two frequency terms  $v \cdot k$  and  $v/2$ . The former term gives quantized frequency  $v_k = v \cdot k$  as distribution in terms of phonons. The latter term gives the lowest possible frequency  $v_0 = v/2$ . In this way, corresponding frequency spectrum is  $(v_0, 3v_0, 5v_0, \dots, v_0(1 + 2k))$ , where  $k = 0, 1, 2, 3, \dots$

However, analogy with the physical model of phonons ends here. Strictly speaking, we cannot straightforwardly to adapt a set of quantized modes of vibrations occurring in a rigid crystal lattice for the economic systems. We have to design our own stylized set of quantized modes of vibrations suitable for simulations of processes taking place in the economic systems.

In our case, we want to have quantized spectrum, because we need fixed and separated frequencies allocated for different attributes (nodes, agents, resources),

---

<sup>18</sup>Virtual space axes are arbitrary chosen by the user. For example, in the investing MAS application, rectangular lattice could have two orthogonal axes for possessed capital and investing strategy.

<sup>19</sup>In physics, a phonon is a quantized mode of vibration occurring in a rigid crystal lattice, such as the atomic lattice of a solid. Phonons play a major role in many of the physical properties of solids, including a material's thermal and electrical conductivities. In particular, the properties of long-wavelength phonons give rise to sound in solids. In insulating solids, phonons are also the primary mechanism by which heat conduction takes place.

but instead of linear we are using natural logarithm to reduce high energy leaps at low  $k$  values, shortening available frequency interval at the same time. For the node  $\Omega_{n,m}$  energy spectrum may look like

$$\begin{aligned} E_k^{n,m}(I^{n,m}, k^{n,m}, v^{n,m}) &\sim \zeta \cdot I^{n,m} \cdot v^{n,m} \cdot \ln(k + e), \\ I^{n,m} &= A^2, \end{aligned} \quad (2.10)$$

where  $\zeta$ —chosen scaling factor,  $I$ —intensity (c.u.),  $A$ —amplitude of oscillation,  $v^{n,m}$ —first harmonic of the system of nodes,  $k$ —spectrum band number, and  $e = 2.71$ . Having Eq. 2.10, we may effectively characterize each system's spectrum in terms of distribution of  $k$

$$D(E_k) \sim D(v_k) \Rightarrow D(k).$$

Actually, spectrum band number  $k$ , having virtual energy spectra described by Eq. 2.10, is the only thing we need to know in order to identify virtual nodes. Whereas, each nodes unique oscillations and corresponding spectral bands are derived by multiplying the first harmonic  $v^{n,m}$  by the factor  $\ln(k + e)$ , which finally gives logarithmic scale for oscillations. Than  $k = 0$ , we obtain

$$E_0^{n,m}(v^{n,m}) = \zeta \cdot I^{n,m} \cdot v^{n,m}. \quad (2.11)$$

which represents each node's  $\Omega_{n,m}$  unique natural oscillation energy. Hence, different nodes have distinct frequencies  $v^{n,m}$ .

There is one major difference between representation of nodes and natural resources in the PIF model. Nodes are constant attributes of the system,<sup>20</sup> whereas, natural resources diminish or replenish themselves according to some time  $t$  dependant functions like<sup>21</sup>

$$I_{R_i} = f_i(E_{R_i}^{n,m}(t)). \quad (2.12)$$

For instance, in the economics domain, natural resources are productive economic sectors, regions, technologies, businesses, or securities like risky shares, government bonds, options, etc., which could generate capital gain or loss depending on initial model setup.

Finally, we have to discuss about agents' spectral energy representation in the PIF. Naturally, we will adapt the same approach as for resources. Let's assume, that agents  $\{A_j\}$  radiate own group of frequencies. One unique frequency band is allocated for each agent, i.e., frequencies only are meant to identify a presents of the particular agent in the PIF.

<sup>20</sup>This is simplification as space metrics may be time dependant too, e.g.  $\vartheta_{G_{N \times M}} = f_t^G(G_{N \times M}(t))$ .

<sup>21</sup>We may employ whatever linear or nonlinear time dependant functions.



$$E_{A_j}^{n,m}(v_{A_j}^{n,m}) \Rightarrow \psi \cdot I_{A_j} \cdot v_{A_j}^{n,m} \cdot \ln(h + e), \quad h = 1, 2, 3, \dots, \quad (2.13)$$

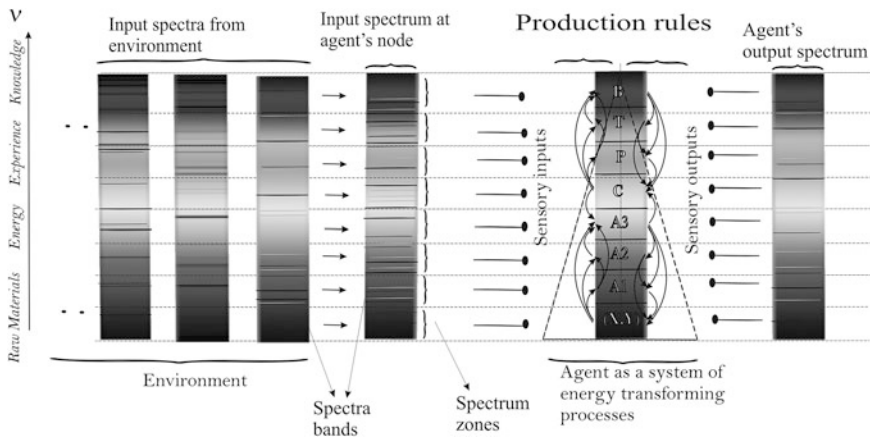
where  $E_{A_j}^{n,m}$ —energy of the agent  $A_j$  and characteristic frequency band  $v_{A_j}^{n,m}$  (i.e., the first harmonic of agents'),  $\psi$ —scaling factor,  $I_{A_j}$ —emission intensity (represents quantity of the given resource) and  $h$ —spectrum band number. As for nodes and resources,  $h$  is the only thing we need to know in order to identify virtual agents. Each agent's unique oscillations and corresponding spectral bands are derived by multiplying the first harmonic  $v_{A_j}^{n,m}$  by the factor  $\ln(h + e)$ .

We imply that  $\min E_{A_j}^{n,m} > \max E_{R_i}^{n,m}$ , i.e., available intervals of frequencies for natural resources and agents do not overlap. Hence, it means a limit for  $i$  (resource spectrum band number). We also assume that agents are located on the nodes only and one node could have only one agent.

In sum, PIF approach allocates unique frequencies for nodes, resources and agents. It also calculates resulting spectrum for each node. Such spectra include all bands coming from all resources, agents and other nodes. Bands do not overlap as they cover different spectral zones, see Fig. 2.3. In addition, we assume that all oscillations are transmitted instantaneously over the whole virtual space. Next, we will discuss wave-like interaction between agents.

## 2.5 Wave-like Interaction Mechanism (WIM)

In the proposed approach, nodes and resources are latent objects. They can only passively emit their own unique natural frequencies in the surrounding PIF. Agents passively emit their unique identifying frequencies too, but essentially they are proactive, i.e., agents, depending on their behavioral rules (internal production rules,



**Fig. 2.4** An agent's production rules, which govern the transformation of internal states, represented as spectra bands

see Fig. 2.4), are capable of absorbing, transforming and emitting different frequencies. This interactive process is twofold: (i) automatic in the form of law, which holds whenever appropriate wave-like conditions are met and (ii) personalized, i.e., it depends on the agent's individual behavioral patterns governed by the oscillating agent model (OAM) rules, see Fig. 2.4. Now, let's take a look at some WIM (wavelike interaction mechanism) processes.

### 2.5.1 *The Latent (Involuntary) Emission and Absorption Process*

Each agent  $A_j$  has a set  $\{\omega_{A_j}\}$  of natural frequencies. At these frequencies, even small incoming periodic oscillations can produce an agent's automatic response in the form of high-amplitude outgoing oscillations because an agent (like other physical systems) transforms and stores incoming energy in the form of natural or resonant frequencies.<sup>22</sup> If outside oscillations match an agent's natural frequency, then his natural stored energy is gradually released to the PIF. The general rule of thumb for the agent's involuntary resonance with surrounding PIF is

- (a) if outside frequencies coincide with the agent's natural frequencies (then the change in the agent's internal energy for period  $T$  is negative  $\Delta E_T < 0$ , i.e., a responsive natural emission is taking place and agent is loosing stored energy)
- (b) if outside frequencies do not coincide with the agent's natural frequencies (then the change in the agent's internal energy for period  $T$  is positive  $\Delta E_T > 0$ , i.e., latent absorption by agent is taking place)

$$\Delta E = \Delta E_{\text{abs}}^f - \Delta E_{\text{emi}}^{\omega_{A_i}} = \begin{cases} < 0, & \text{if } f = \omega_{A_i} \\ > 0, & \text{if } f \neq \omega_{A_i} \end{cases}. \quad (2.14)$$

For the agent  $A_j$  absorbed energy is stored as free energy in the spectral range  $\{\omega_{A_j}\}$  of the agent's natural frequencies

$$\Delta E \Rightarrow \Delta E^{\{\omega_{A_i}\}}, \quad (2.15)$$

---

<sup>22</sup>Resonant phenomena occur with all types of vibrations or waves: there is mechanical resonance, acoustic resonance, electromagnetic resonance, NMR, ESR and resonance of quantum wave functions. When damping is small, the natural frequency is approximately equal to the agent's resonance frequency.

then  $\Delta E > 0$ .

The agent's internal energy (see Eq. 2.13)

$$\begin{aligned}
 E_{A_j} &= \sum_{h=0}^H E_{A_j}^{n,m}(v_{A_j}^{n,m}) \\
 &= \sum_{h=0}^H \psi \cdot I_{A_j} \cdot v_{A_j}^{n,m} \cdot \ln(h+n), \quad h = 1, 2, 3 \dots H
 \end{aligned}
 \tag{2.16}$$

### 2.5.2 The Active (Voluntary) Emission and Absorption Process

In the proposed approach, agents have a mechanism to look for useful information in the surrounding PIF. They inherit this property from a priori settled individual behavioral rules.<sup>23</sup>

Acquiring meaningful (successful) information means adopting a new behavioral pattern. This comes at a price, however. For instance, let us say agent  $A_I$  wants to buy information  $P$  (where  $P$ —stands for the agent's  $A_2$  behavioral parameters set) paying some amount of his own capital  $K$  (equivalent to the energy  $E_K^{n,m}(v_K^{n,m})$  where  $K \in R_i$  to the selling agent  $A_2$

$$\begin{aligned}
 E_{A_1}^{emi}(v_K) &\xRightarrow{K \text{ transfer}} E_{A_2}^{abs}(v_K), \\
 E_{A_1}^{abs}(v_P) &\xleftarrow{P \text{ transfer}} E_{A_2}^{emi}(v_P),
 \end{aligned}
 \tag{2.17}$$

where

$$\begin{aligned}
 \Delta E_{A_1}(P \rightarrow K) &= E_{A_1}^{abs}(v_P) - E_{A_1}^{emi}(v_K) < 0, \\
 \Delta E_{A_2}(K \rightarrow P) &= E_{A_2}^{abs}(v_K) - E_{A_2}^{emi}(v_P) > 0, \\
 \Delta E_{A_1}(P \rightarrow K) + \Delta E_{A_2}(K \rightarrow P) &= 0.
 \end{aligned}
 \tag{2.18}$$

The agent's efficiency depends on his spectral coherence with the global criteria (e.g., market rules) which specify some spectrum measures like minimum internal energy (e.g., available capital, etc.) needed for survival. Extremely coherent agents (i.e., successful investment strategies in the current application case) can be rewarded, while extremely incoherent agents can be removed from the simulation process.

---

<sup>23</sup>The possession of meaningful information gives a certain advantage. For instance, acquiring information from PIF about successful investment strategy (i.e. a portfolio management rule) and adopting it gives a currently less successful agent a good prospect to becoming successful in terms of capital accumulation in the future.

In sum, this chapter presents an outline of a conceptually new approach for simulating local and global behavioral patterns observed in information-rich social networks. The main ideas cover the (i) pervasive information field (PIF), (ii) oscillating agent model (OAM), and (iii) the agents' wave-like interaction mechanism (WIM). The conceptual considerations provided can be interpreted as an initial first 'take' on the methods used for social phenomena simulation. More specific outlines and their explanatory sources are provided in the next chapters.

Hence, this chapter ended with the proposition of the stylized phonons' model, which quantifies agents' oscillatory energy and implements energy-information exchange mechanism. In the proposed model of harmonic oscillators, each agent absorbs incoming wave packets, linearly superposes them (producing unique spectra), and then transmits them to the environment. Putting mathematical notations aside, with the help of stylized production rules, we can obtain some quantitative means of modeling energy and information exchange mechanism between oscillating agents. The main drawback of such an approach, however, comes up from hypothetical and stylized modeling, which is based on the theoretical assumptions of the oscillatory nature of social agents' states. The next chapter makes some further considerations and assumptions in order to deepen and broaden the oscillations based approach.

Introducing the Oscillations Based Paradigm

The Simulation of Agents and Social Systems

Plikynas, D.

2016, XXIV, 325 p. 97 illus., 16 illus. in color., Hardcover

ISBN: 978-3-319-39039-0