Climbing the right hill – an evolutionary approach to the European market of electricity

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Abstract
This article studies social change as an evolutionary adaptive walk in rugged landscape, with the assumption of collective intelligence, in the view of optimizing the share of electricity in the consumption of energy, and the share of renewable sources in the generation of electricity. An original method is introduced, where a neural network is used to produce alternative social realities out of the source empirical dataset. Euclidean distance between those alternative sets, and the original one is used as basis for assessing collectively pursued outcomes. Variance in Euclidean distance between variables of the set is used to assess the intensity of epistatic interactions between social phenomena represented by quantitative variables. The method is tested on a sample of 28 European countries, between 2008 and 2017, in the presence of market imperfections in the retail pricing of electricity. The key, energy-relevant variables seem to be instrumental to the pursuit of other social values, and those values seem to be focused on the intensity of human labour, and its remuneration.

Keywords: evolutionary change, energy, renewable energies, energy market

JEL codes: C15, C18, C33, C45, Q4, Q43

Introduction

As a civilization, how capable are we to face, mitigate and prepare for climate change? How can we use to the best the characteristic cultural traits of our societies so a as to face this challenge? This is probably one of the most salient questions in social sciences, presently, as radical climate action seems to require radical social change, and, as a civilization, we have simply never accomplished a change both so deep and so quick. If we want people to change their ways, we need to utilize their existing values and patterns of behaviour, whilst combining them with new elements, proper to tackle the challenge ahead. This article introduces a method to identify - through the use of quantitative data in a neural network - the collective values pursued by a society, as regards the market of energy.

Our civilization needs, amongst other things, two overlapping types of change regarding energy: increasing the share of electricity in the overall basket of energy consumed and increasing the share of sources other than fossil fuels in the generation of electricity. Can we reasonably assume that – as a civilisation – we can and will consistently, collectively pursue those goals over the years to come? The author's previous research regarding energy intensity and energy efficiency indicates that our civilisation is not really ready for being a purposefully energy saving one (Wasniewski 2017, 2019).

We can collectively pursue goals and values without being aware of pursuing them. Objective outcomes of our actions are something distinct from the culturally communicated purpose. One of the most important applications of that distinction is visible in collective learning. Historically, one can observe that puzzling tendency of mankind to put a lot of resources into projects of apparently questionable utility: the pyramids, the medieval cathedrals etc. Why going to such lengths in order to build a structure where no one is going to live or do any kind of socially productive activity? Answer: in order to learn architecture, physics, chemistry, engineering, project management etc. Yet, the 'official' logic behind those grand ventures was different. Officially, our ancestors were building those magnificent structures in order to better practice their religions. Whoever would have claimed they are building a cathedral in order to learn better measurement of rigid tension in a wall would have had probably been burnt at the stake. Another example is Abraham De Moivre's 'Doctrine of Chances': as one reads this treaty, it jumps to the eye that gambling has been a big experimental field for developing the theory of probability, which, in turn, allows us today to perform quantum computation.

Social sciences are largely based on the assumption of tacit coordination: we can do things together without being fully aware we are doing them together or even whilst thinking we oppose each other (e.g. Kuroda & Kameda 2019). In the presence of quick growth in population, each consecutive generation brings greater a number of people than the previous one, and greater a probability of new social roles emerging. Emergent social roles are associated with increased vertical social mobility and with the resulting hierarchical rivalry, whilst, in the same time, offering the possibility to develop new technologies, instrumental to performing these roles (e.g. Gil-Hernández et al. 2017). This is just one example of how human societies trigger faster collective learning in the presence of more humans being around and in need of scarce resources.

In the market of energy, the connection between small-scale installations based on renewable sources of energy (RES), on the one hand, and the technologies of energy storage, on the other hand, makes a good example of tacit coordination and learning between technologies. Small scale RES installations bring low-voltage electricity, which, in turn opens a market for low-voltage technologies of storage, whence the spectacular development of batteries (Abrell et al. 2019; Sreekanth et al. 2019; Schmidt et al. 2019). More advances in the technology of batteries means, in reciprocal reaction, better grounds for small scale RES installations. Still, investment in renewable energies seems to convey high an uncertainty (Liyun Liu et al. 2019), which implies other risk factors at play. Recent research on the prices of electricity shows that even apparent volatility can hide deeper social coordination. Borovkova & Schmeck (2017) propose a model for studying electricity prices, based on stochastic time change. These authors convincingly prove that electricity prices, beyond the apparent aleatory change along geometric Brownian motion, change according to an Orstein-Uhlenbeck process, with a strong attractor observable as significant mean-reversion. Similar results are communicated by de Oliveira et al. (2019). Significant mean-reversion is informative, in turn, about some kind of underlying, durable economic equilibrium(s). In economics, an equilibrium is an instance of the same tacit coordination as exemplified before: we cooperate without necessarily knowing we do.

This article introduces the concept of **collective intelligence**, defined as the capacity for social evolutionary tinkering (Jacob 1977) through tacit coordination, such that the given society displays social change akin to an adaptive walk in rugged landscape (Kauffman & Levin 1987;

Nahum et al. 2015). Each distinct state of the given society (e.g. different countries in the same time or different moments in time as regards the same country) is interpreted as a vector of observable properties, and each empirical instance of that vector is a 1-mutation-neighbour to at least one other instance. All the instances form a space of social entities. In the presence of external stressor, each such mutation (each entity) displays a given fitness to achieve the optimal state, regarding the stressor in question, and therefore the whole set of social entities yields a complex vector of fitness to cope with the stressor. The assumption of collective intelligence means that each social entity is able to observe itself as well as other entities, so as to produce social adaptation for achieving optimal fitness. Social change is an adaptive walk, i.e. a set of local experiments, observable to each other and able to learn from each other's observed fitness. The resulting path of social change is by definition uneven, whence the expression 'adaptive walk in rugged landscape'. There is a strong argument that such adaptive walks occur at a pace proportional to the complexity of social entities involved. The greater the number of characteristics involved, the greater the number of epistatic interactions between them, and the more experiments it takes to have everything more or less aligned for coping with a stressor.

Collective intelligence, as a theoretical construct, might be an interesting, and developmental compromise between agent-based theories in economics, and models of general equilibrium. Some literature suggests the need of such a synthesis (see for example: Babatunde et al. 2017). Yet, collective intelligence is a hypothesis rather than a theory. On the one hand, since Emile Durkheim, social sciences acknowledge the potent impact of cultural constructs upon human behaviour. Yet, defining intelligence in itself is tricky. Lavniczak and Di Stefano (2010) claim that intelligence requires the existence of a cognitive agent, which, in turn, should be autonomous, i.e. able to interact with its environment and with other agents. This autonomy translates into 5 specific cognitive functions: a) perceiving information in the environment and provided by other agents b) reasoning about this information using existing knowledge c) judging the obtained information using existing knowledge d) responding to other cognitive agents or to the external environment, as it may be required and e) learning, i.e. changing (and, hopefully augmenting) the existing knowledge if the newly acquired information allows it. Among those six characteristics (i.e. one general and five specific ones), when studying collective intelligence in human societies, we can unequivocally tick just the first box, and the last one, i.e. perception, and the capacity to learn. When we study collective intelligence possibly represented by quantitative variables, aggregated into databases, those sets of numbers are supposed to be representative for a complete society, global, continental or national. How can it be autonomous? Completely, on the other hand, and not at all, on the other hand. Do we communicate with other civilisations? Probably not yet, although we communicate with the natural environment. As for collective reasoning, judgment and response, these are arguably black boxes. Manifestations of social behaviour, such as, for example, the average wage, change from year to year, which suggests that some people do something in response to something else, and those people belong to a collective intelligence. Doing something meaningful implies, most likely, some reasoning and some judgment, and yet we do not have a clear map of these functions at the collective level. We suppose it happens, but we don't know how.

If we approach collective intelligence as entanglement of individual nervous systems, assuming the existence of autonomous cognitive agents is questionable. There are strong theoretical and empirical grounds for treating any neural function in a human brain as a network occurrence, where the construct of autonomous cognitive agent is a convenient illusion rather than a true representation of reality. The so-called 'Bignetti model' is one of the best-known approaches in this theoretical stream (Bignetti 2014; Bignetti 2018; Bignetti et al. 2017): whatever happens in observable human behaviour, individual or collective, has already happened neurologically beforehand.

This cursory review of the issue suggests an interesting question: how strong the assumptions formulated for studying collective intelligence should be? Two opposite, theoretical paths open up. On the one hand, we can go towards as weak assumptions as possible, in order to make the corresponding research immune to false ideas. The so-called ‘swarm theory’ is a good example (Stradner et al. 2013). Collective intelligence occurs even in animals as simple neurologically as bees, or even as the Toxo parasite; claiming autonomous cognitive functions in them is truly a strong assumption. Still, they manifest collective intelligence by shifting between different levels of coordination: from deterministically coordinated action (behaviour A in one specimen always provokes behaviour B in another specimen), through correlated action (behaviour A is significantly correlated with behaviour B), all the way up to randomly coupled action (behaviour A provokes a loose, apparently random range of responses in other specimens). The swarm theory claims that social learning is possible precisely by shifting between those different levels of coordination, and demonstrable shift of this kind is enough to assume that a society is collectively intelligent.

On the opposite end of the theoretical spectrum, we have approaches such as that presented by Doya & Taniguchi (2019). They claim that intelligence, whether individual or collective, is endowed with many layers. The capacity to reproduce something complex is one layer, arguably the crudest one. Developmental intelligence means the capacity to create new symbolic models of reality and figure out something practical on that basis. If we produce many different versions of empirical reality, the most functional one (i.e. the one that brings the best immediate reward) reflects the most basic level of collective intelligence. More abstract levels of intelligence can emerge, as we solve more and more complex problems through theory. Quantum physics are an excellent example: very abstract, symbolic representations of reality serve to solve very practical issues, such as the best way to make good steel. The distinction introduced by Doya and Taniguchi suggests two distinct levels of abstraction in studying the human collective intelligence at work. On the one hand, we can adopt the reductionist approach and test human societies for the presence of recurrent, swarm-like patterns of shifting coherence in social coordination. Down this avenue, we hypothesise the working of collective intelligence understood crudely and elementarily.

It is further assumed that human societies are collectively intelligent about the ways of generating and using energy: each social entity (country, city, region etc.) displays a set of characteristics in that respect. There is a body of historical and paleontological evidence that accurate adjustment of energy balance was one of the key factors in the evolutionary success of humans, both at the level of individual organisms and whole communities (Leonard, Robertson 1997; Robson, Wood 2008; Russon 2010). We can be annoyed by the allegedly snail’s pace in technological change regarding energy, but we need to keep in mind that, seen as an adaptive walk of a collective intelligence, it happens in a very rugged landscape, and the ruggedness of that landscape comes from the complexity of human societies. Quite substantial a body of research suggests that complexity in organizations can seriously slow down their pace of adaptation, even to the point of dysfunctionality (e.g. Baden-Fuller & Stopford 1992; McKelvey 1999). From the standpoint of biology, there is a well-founded claim that complex organisms can adapt by internalizing an external stressor, in the form of internal epistatic interactions, without really increasing their overall fitness to cope with the stressor (Kauffman 1993). Still, other research suggests that when such organisms endowed with complex epistatic interactions adapt at all, they develop stronger fitness than structures relatively poorer in epistasis (Skellet et al. 2005). In order to illustrate this specific aspect as regards the market of energy, it is worth citing the otherwise quite fruitful path of research, labelled as MuSIASEM methodological framework, which studies aggregate use of energy in an economy as a metabolic process: the (e.g. Andreoni 2017; Velasco-Fernández et al. 2018).

Adaptive walks in rugged landscape consist in overcoming environmental challenges in a process comparable to climbing a hill: it is both an effort and a learning, where each step sets a finite range of possibilities for the next step. Each adaptive rearrangement of vital characteristics in the given space of entities creates the starting point for further rearrangements. Features such as the relative height of the climb, its slope, as well as the general difficulty of the terrain to cover are exogenously given. There is one given path uphill, which can be deemed optimal. Still, the actual exact path taken by the entities in question most likely diverges from the optimal one ((Skellet et al. 2005 op. cit.). The entities involved climb the hill anyhow they can.

Assuming collective intelligence at work in human cultures, defined as adaptive walk in rugged landscape, an interesting question arises: what is exactly the hill we are climbing as a civilization? Do we climb the hill of energy-efficiency, the one of renewable energy, or maybe some other hill? Does our path uphill include optimizing the retail prices of electricity, the share of renewables, or the overall consumption of energy? We certainly would like to believe we do, but do we really? How exactly is energy management entangled, in human societies, with other social phenomena, and how does it affect the fitness of human social structures to cope with climate change as external stressor? Research presented in this article aims at checking and exploring the **hypothesis that collectively intelligent adaptation in human societies, regarding the ways of generating and using energy, is instrumental to the optimization of other social traits**.

The method

The method presented here below applies the theory of collective intelligence, understood as adaptive walk in rugged landscape, to typical datasets used in social sciences, i.e. pooled sets of 'space-time' specific observations, such as 'country-year' ones. This method gives interesting results when applied jointly with other types of quantitative analysis, which will be illustrated with the empirical research presented in further sections. When the connection between phenomena is studied as regression of the correspondingly informative, quantitative variables, the distinction between the sides of equation is largely arbitrary. Usually, the variable informative about a phenomenon we want to optimize is being put on the left side, as the dependent outcome, and other variables are labelled as its independent factors. Transformations such as lagged values can help to ground the claim that variables on the right side independently cause change in the variable on the left side. Still, causality is different from purpose. An acceptably robust model based on regression states the former, but not the latter. In that context, it is interesting to use quantitative data so as to find out the collectively pursued purpose of a society.

We can imply that countries learn from one another (i.e. each national population can learn from all the other national populations), and they experiment with themselves, all in the form of an adaptive walk in rugged landscape. Therefore, when space of social entities is described as a set $\boldsymbol{X}$ of empirical observations grouped into $\boldsymbol{n}$ variables and $\boldsymbol{m}$ phenomenal occurrences (records), it is possible to assume that the set X gives the account of an adaptive walk performed by the social entities involved in rugged landscape.

At this point, it is useful to return to the theoretical assumption mentioned in the introduction, namely that complex entities can internalize an external stressor as they perform their adaptive walk. Therefore, observable variance in each variable x_i in the set X can be considered as manifestation of such internalization. In other words, observable change in each separate variable can result from the adaptation of social entities observed to some kind of 'survival imperative'. Mathematically, any such set X of empirical observations grouped into n variables and m phenomenal occurrences (records), can be transformed into n congruent sets S_i through an experimental procedure performed in a neural network, where each congruent set S_i represents a hypothetical situation when one among n variables of the set X is taken as the output of the neural network, and the remaining $n-1$ variables are assumed to be the input. In plain words, such a congruent set S_i is a specific mutation of the set X, oriented on optimizing the specific variable x_i. Variable x_i is the algorithmic equivalent of an internalized stressor, which the social entities observed strive to adapt to.

Each congruent set S_i is produced with the same logical structure of the neural network, i.e. with the same procedure of estimating the value of output variable, valuing the error of estimation, and feeding the error forward into consecutive experimental rounds. This, in turn, represents a hypothetical state of nature, where the social system represented with the set X is oriented on optimizing the given variable x_i, which the corresponding set S_i is pegged on as its output. Please, note that the number of congruent sets S_i is n, i.e. the same as the number of variables in the source set X. In other words, the neural network (a multi-layer perceptron) simulates a process, where one precise trait of the species, i.e. the variable selected as the output one, is the outcome to optimize, and all the other variables in the dataset (i.e. all the other characteristics of the species) are instrumental to that optimization. The output variable represents the hill to climb, and observable changes in the input variables represent the series of small steps taken to climb the hill. Each step consists in testing small mutations in the input, i.e. in the characteristics instrumental to climbing the hill. Each clone S_i of the basic dataset represents a path up a **different hill**.

For each variable x_i, and each set S_i, the neural network produces, an alternative mean value $avg(S_i;x_i)$ of observations standardized over the variable-specific maximum value $max(X; x_i)$, in the source set X. Each transformed set S_i (i.e. pegged on the given variable x_i) can be assessed as for its similarity with the source set X, by calculating standardized Euclidean distance between the respective vectors of mean values both sets, as in equation (1). The smaller the Euclidean distance, the greater the similarity. The hierarchy of sets S_i as regards their Euclidean similarity to the source set X is informative about the hierarchy of values pursued by the society described with X, when values are understood as variables to optimize. The specific set S_i, which, among n sets S, displays the closest Euclidean distance to the source empirical set X, is assumed to represent the most accurately the orientation of collective intelligence in the observed society. As regards the theory of neural networks, this approach is based on the type of algorithm known as Gaussian mixture (see for example: Zhang & Cheng 2003; Koolagudi et al. 2012).

$$E(X;S_i) = \frac{\sum_{i=1}^{n}\sqrt{\left[\frac{avg(S_i;x_i)*\max(X;x_i)}{avg(X;x_i)}-1\right]^2}}{n} \qquad (1)$$

The neural network produces the alternative mean value ***avg(S_i;x_i)*** by learning through ***m*** ordered experimental rounds, where the number ***m*** of rounds and their order are the same as the number and order of records in the source dataset ***X***. Each set ***S_i*** must contain the same number ***m*** of phenomenal occurrences and they must be arranged in the same order. The only attribute of the learning process that changes across different sets ***S_i*** should be the variable chosen as the output one, thus as the desired collective outcome, whilst the spatio-temporal order of empirical experiences to learn from should remain constant across all the sets ***S_i***. The learning process in itself consists in estimating the value of the output variable $\boldsymbol{x_o}$ over ***m*** ordered phenomenal occurrences in the dataset ***X***, and calculating the error of estimation as regards the real value of output variable, as given in the source dataset ***X***. Each consecutive experimental round in the neural network takes into account errors recorded in previous rounds.

The error observed by the neural network in a given experimental round $\boldsymbol{p_{j-1}}$ is fed forward into the next experimental round $\boldsymbol{p_j}$ at two levels. Firstly, error is considered as an amount of information, and as such should be added to the information we already have in hand, thus to the value of each variable in the source set ***X***, as in equation (2). Secondly, error is an event, which should be taken into account when estimating the output variable $\boldsymbol{x_o}$ in the next experimental round. The function of neural activation is the hyperbolic tangent $\frac{e^{2h}-1}{e^{2h}+1}$, as in equation (3). When we learn by trial and error, a hypothetical number $\boldsymbol{e^{2h}}$ measures the force which the neural network reacts with to a complex stimulation from a set of variables $\boldsymbol{x_i}$. The '$\boldsymbol{e^2}$' part of that hypothetical reaction is constant and equals $\boldsymbol{e^2 = 7{,}389056099}$, whilst $\boldsymbol{h}$ is a variable parameter, specific to the given phenomenal occurrence $\boldsymbol{p_j}$ in the dataset ***X***, as expressed through equation (3). Each variable $\boldsymbol{x_i}$, in the given phenomenal occurrence $\boldsymbol{p_j}$, is a single neural stimulus. The neuron, represented in equations (3) and (4), experiments with various degrees of importance (various weights) attached to each individual stimulus. Hence, the neuron reacts to a basket of stimuli, which it experiments with as for their respective importance. The factor ***R ~ U([0,1])***, thus a pseudo-random number in the interval between 0 and 1, represents that purely aleatory experimentation.

Unless the network standardizes the component factors of the parameter $\boldsymbol{h}$, the latter is roughly proportional to the number of variables in the source empirical set ***X***. The more complex the reality we represent with the set ***X***, i.e. the more variables are there, the greater is the value of $\boldsymbol{h}$. In other words, the more complexity, the more is the neuron, based on the expression $\boldsymbol{e^{2h}}$, driven away from its constant root $\boldsymbol{e^2}$. Complexity in variables induces greater swings in the hyperbolic tangent, i.e. greater magnitudes of error, and, consequently, longer strides in the process of learning.

The ***V[x_i(p_j)]*** factor in equation (4) is a local, variable-specific and observation-specific parameter, and is further expanded in equation (5). It corresponds to the so-called fitness function: in each phenomenal occurrence each local value of variable $\boldsymbol{x_i}$ is gauged as for its Euclidean distance from the remaining ***n – 1*** variables. From the point of view of learning and collective intelligence, ***V[x_i(p_j)]*** is a measure of coherence between variables in each consecutive experimental round. It corresponds to the assumption that any society both optimizes itself so as to achieve a desired outcome, and keeps a certain level of internal coherence, whilst having to relax that coherence every now and then to allow new learning. Each variable $\boldsymbol{x_i}$ in the set ***X*** is observed as for variance in its local fitness function, across different sets ***S_i***, i.e. across perceptrons pegged on different variables. From the standpoint of adaptive walks in rugged landscape, variance observed in the fitness function ***V[x_i(p_j)]***

measures the magnitude of change in epistatic connections, which the given variable maintains with other variables in the set. Relatively high a variance in $V[x_i(p_j)]$ allows guessing significant change in those epistatic connections, as the neural network learns. Variables displaying such high variance in $V[x_i(p_j)]$ are pivotal to changes, which occur along the path of adaptive walk in rugged landscape. Translated into the toolbox of social sciences, this line of logic can be connected to Paul Krugman's claim that when different factors of economic geography change at different paces, the one displaying the fastest pace – thus being able to sort of get particularly far away from the others – is the one that shapes the landscape (Krugman 1991). Further, it allows hypothesising that some social phenomena tend to be significant factors of change when they demonstrate the capacity to increase their Euclidean distance from other phenomena. This is the so-called swarm theory (de Vincenzo 2018).

$$avg(S_i; x_i) = max(X, x_i) * \frac{\left\{\frac{x_i(p_1)}{max(X,x_i)} + \sum_{j=1}^{m-1}\left[\frac{x_i(p_j)}{max(X,x_i)} + e(p_{j-1})\right]\right\}}{m} \quad (2)$$

$$e(p_j) = x_o(p_{j-1}) - \left\{\frac{e^{2h}-1}{e^{2h}+1} * \left[1 - \left(\frac{e^{2h}-1}{e^{2h}+1}\right)^2\right]\right\} \quad (3)$$

$$h = \sum_{i=1}^{n} R \sim U([0,1]) * V[x_i(p_{j-1})] * \left[\frac{x_i(p_j)}{max(X,x_i)} + e(p_{j-1})\right] - V[x_o(p_{j-1})] * \frac{x_o(p_j)}{max(X,x_o)} \quad (4)$$

$$V[x_i(p_j)] = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n-1}\sqrt{\left[\frac{x_i(p_j)}{max(X,x_i)}(j) - \frac{x_k(p_j)}{max(X,x_k)}(j)\right]^2}}{n+1} \quad (5)$$

After having run the procedure described above, and formalized in equations (1) – (5), each variable x_i in the dataset X acquires a vector of descriptive parameters, namely: i) the Euclidean distance $E(X; S_i)$ between the set S_i pegged on this specific variable x_i as its output, and the original empirical set X; this is informative about how important the variable x_i is as social outcome to optimize, and ii) a vector of variances in the x_i-specific fitness function $V[x_i(p_j)]$ across all the n sets S_i; this, in turn, indicates the importance of x_i as factor of change. Thus described, each such variable x_i can be assessed, in the first place, as for its relative importance as collective outcome, which the collective intelligence studied strives to optimize, as well as regards its importance as factor of adaptive change, through epistatic interactions inside the social entities studied. The underlying assumption is the highest the variance, the greater the probability that phenomena represented by the given variable are drivers of social change. Seen from perspective of equations (3) – (5), relatively high a variance in the fitness function of a particular variable means that the same variable contributes to create variance in the parameter

$\boldsymbol{h}$, as in equation (4), and thus makes the neuron $\frac{e^{2h}-1}{e^{2h}+1}$ swing particularly far from its constant base.

The vector of variances in the x_i-specific fitness function $V[x_i(p_j)]$ across the n sets S_i has another methodological role to play: it can serve to assess the interpretative robustness of the whole complex model. If, in each set S_i, thus across neural networks oriented on different outcome variables, the given input variable x_i displays a pretty uniform variance in its fitness function $V[x_i(p_j)]$, the role played by x_i as pivot in epistatic interactions is relatively the same, whatever the collective outcome pursued. If all or most of variables display such uniformity, it allows assuming that equations (2) – (5), sequenced into a neural network, work in the same way in all the 'clone' sets S_i. In other words, the collective intelligence represented in equations (2) – (5) performs its adaptive walk in rugged landscape coherently across all the different hills considered to walk up. Therefore, a coherent pattern of evolutionary social change can be guessed in the social structure, which the source empirical data refers to.

Conversely, should all or most variables x_i, across different sets S_i, display noticeably disparate variances in $V[x_i(p_j)]$, different a pattern of epistatic interactions can be guessed as regards different outcomes pursued by the neural network of equations (2) – (5). In that case, the network represents a collective intelligence which adapts in a clearly different manner to each specific outcome (i.e. output variable). The pattern of social change, understood as evolutionary adaptive walk, is not really coherent. It might mean, for example, that the social structure under scrutiny is changing so profoundly that even its very pattern of transformation is under construction.

Another test for robustness, possible to apply together with this method, is based on a category of algorithms called 'random forest' (see for example: Serras et al. 2019; Baba & Sevil 2019). The general idea is that in a set of country-year observations, the neural network performs its learning across ordered data: country A in year m_1 first, then country A in year m_2, a few steps further it is the turn of country B in year m_1 etc. The order of data presented for learning can influence the results. Pooled datasets of the 'country–year' type are commonly ordered across countries, in the first place, and secondarily over consecutive years. The neural network learns 'inside' one country, just to apply that learning to the next country in line etc. Had it been a collective intelligence at work, it would learn by absorption of experience from country to country in relatively long jumps over time, without much inter-country communication in the short perspective. In order to test for this specific phenomenon, a comparative, randomized dataset is created – let's call it X_R – by stacking many quasi-random permutations of the source set X. The procedure described earlier, i.e. equations (2) – (5) run in a sequence of neural network, and equation (1) used as assessment of similarity. The results are compared against those obtained with the source set X. The most basic formal test is, once again, that of Euclidean distance in the spirit of equation (1). If the results derived from the randomized set X_R differ significantly from those based on the source set X, the order of data has obviously impacted the representation of collective intelligence at work in the given social structure. Should there be no such significant difference, the order of phenomenal occurrences has no importance in the given case.

The dataset

The method introduced in the previous section has been applied to the **European market of energy**, with a special focus on two variables, which the author perceives as crucial for tackling climate change: **a) the share of renewable energy in the total output of electricity, and b) the share of electricity in the total consumption of energy**. The reason for choosing the European market is both personal, and general. Europe is author's home continent, and the European market of energy displays an interesting imperfection. European households systematically overpay for electricity, per kilowatt hour, as compared to other groups of users (EUROSTAT). At the scale of the whole EU28, the average price fork between the retail price paid by household users for 1 kWh, as compared to non-household final users, has climbed from €0,07 in 2008 to €0,13 in 2019. As price data is enriched with that regarding aggregate consumption of energy, the corresponding aggregate cash flow, once again for the entire EU28, can be estimated at € 57 942,53 mln in 2008, and € 95 881,63 mln in 2017 (these estimations are based on the assumption that the share of electricity in the final energy consumption in households is the same as in the total consumption of energy across all sectors). So as to place those aggregate numbers in a broader context, entire worldwide investment in renewable energies in 2017 was around $279 bln (Frankfurt School-UNEP 2018). For reasons that still remain to be explained fully, the market imperfection in question is deepening.

Hence, we have a market of energy with goals to meet regarding the local energy mix, and with a significant disturbance in the form of market imperfections. Coherently with the method presented before, the two key variables under investigation - the share of renewable energy in the total output of electricity, and the share of electricity in the total consumption of energy – have been placed in a broader context of socio-economic factors from the publicly available database Penn Tables 9.1. (Feenstra et al. 2015). Additionally, data has been enriched with three variables, which proved significant in the author's previous research (Wasniewski 2019 op. cit.): total national consumption of energy as scale factor for the market of energy, the number of resident patent applications, as published by the World Bank, the coefficient of resident patent applications per 1 mln people, and the coefficient of capital stock per 1 resident patent application. These two coefficients are author's own calculations, on the grounds of other variables in the database. **Table 5**, in the Appendix, provides the complete list of variables covered by the source empirical set ***X***.

The time-frame of observation in the dataset is consistent with the observability of price imperfections in the market of electricity, and of their aggregate capital counterpart. Whilst EUROSTAT publishes data regarding the prices of electricity up to the current ones in 2019, data regarding quantities is quite disparate after 2017. Hence, the time frame of observation extends from 2008 through 2017. The sample of countries consists in: Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom, Norway, and Turkey. Given this scope in space and time, the resulting empirical set ***X*** consists of ***m = 300*** observations (phenomenal occurrences). Observations are grouped in the classical structure 'country – year'. The underlying assumption as regards the collective intelligence of that set is that each country learns separately over the time frame of observation (2008 – 2017), and once one country develops some learning, that experience is being taken and reframed by the next country etc. The full set, in Excel format, is accessible via the following link to the author's scientific blog: https://discoversocialsciences.com/wp-content/uploads/2019/11/Database-300-prices-of-electricity-in-context.xlsx .

The comparative set X_R has been created as a sequence of 10 stacked, pseudo-random permutations of the original set **X** has been created as one database. Each permutation consists in sorting the records of the original set **X** according to a pseudo-random index variable. The resulting set covers **m = 3000** phenomenal occurrences. This set is accessible, just as the source set **X**, in Excel format via link to the author's scientific blog: https://discoversocialsciences.com/wp-content/uploads/2019/11/Database-3000-randomized-prices-of-electricity-in-context.xlsx

The formal test of Euclidean distances, according to equation (1), yields a hierarchy of alternative sets S_i, as for their similarity to the source empirical set X of ***m= 300*** observations. This hierarchy represents the relative importance of variables, which each corresponding set S_i is pegged on. The variable being the output x_o of the set S_i yielding the greatest similarity to the original set X is retained as the most important social outcome optimized by the collective intelligence represented by the set X. The same variable is then pegged in the set X_R of ***m = 3000*** randomized observations as the output x_o, and the neural network runs its learning, according to equations (2) – (5). The vector of mean values in the corresponding derived set $S(X_R)$ represents the plausibly likely future state of the social reality represented by the source set X.

The detailed descriptive statistics of the dataset at hand are available at https://discoversocialsciences.com/wp-content/uploads/2020/02/Descriptive-statistics-of-the-300-Europe-energy-dataset.xlsx . Here below, Table 1 highlights the descriptive statistics of the four key variables regarding the European market of energy: a) the price fork in the retail market of electricity (€) b) the capital value of cash flow resulting from that price fork (€ mln) c) the share of electricity in energy consumption (%) and d) the share of renewables in electricity output (%). None of these 4 variables seems having been generated by a 'regular' Gaussian process: they all produce definitely too much outliers for a Gaussian process to be the case. That contrasts with the descriptive statistics of other variables in the dataset, the 'regulars' such as GDP or price levels. These latter variables seem to be distributed quite close to normal, and Gaussian processes can be assumed to work in the background. This is a typical context for evolutionary adaptive walk in rugged landscape. An otherwise stable socio-economic environment gets disturbed by changes in the energy base of the society living in the whereabouts. As new stressors (e.g. the need to switch to electricity, from the direct combustion of fossil fuels) come into the game, some 'mutant' social entities stick out of the lot and stimulate an adaptive walk uphill.

Table 1 – Descriptive statistics of variables pertinent to the market of energy, in the dataset studied (EU, N = 300)

	Price fork (€)	**Capital value of the price fork (€ mln)**	**Electricity in energy consumption (%)**	**Renewables in electricity output %**
Mean	0,08	2 755,04	0,23	0,28
Standard Error	0,0029	300,78	0,0043	0,0131
Median	0,07	1 003,24	0,21	0,21
Standard Deviation	0,05	5 209,68	0,08	0,23
Sample Variance	0,0026	27 140 760,88	0,01	0,05

Kurtosis	1,75	15,94	4,73	1,18
Skewness	1,17	3,78	2,01	1,27
Range	0,25	32 970,34	0,39	0,99
Minimum	(0,0036)	(24,72)	0,13	0,0005
Maximum	0,25	32 945,62	0,53	0,99

The method presented in this article is supposed to be complementary with other quantitative analyses. Therefore, in the present section, devoted to the dataset studied, the reader will further find content typical for a 'Results' section, i.e. a cursory look at correlations and linear regressions. From the perspective of this specific method, these are attributes of the data studied – they are informative about its structure – rather than results as such. The next step in preliminary exploration of the dataset at hand is the analysis of Pearson correlation coefficients. The full matrix of those coefficients is downloadable from: https://discoversocialsciences.com/wp-content/uploads/2020/02/Correlation-matrix-Dataset-Europe-Energy-300.xlsx . Interestingly, the phenomena assumed to be a disturbance, i.e. the discrepancy in retail prices of electricity, as well as the resulting aggregate cash flow, are strongly correlated with many other variables in the dataset. Perhaps the most puzzling is their significant correlation with the absolute number of resident patent applications, and with its coefficient denominated per million of inhabitants. Apparently, the more patent applications in the system, the deeper is that market imperfection. Another puzzling correlation of these variables is the negative one with the variable AVH, or the number of hours worked per person per year. The more an average person works per year, in the given country and year, the less likely this local market is to display harmful differences in the retail prices of electricity for households. On the other hand, variables which we wish to see as systemic – the share of electricity in energy consumption and the share of renewables in the output of electricity – have surprisingly few significant correlations in the dataset studied, just as if they were exogenous stressors with little foothold in the market as for yet.

It is instructive to have a look at linear regression models built on the base of the correlations observed. Tables 2, 3, and 4 provide the characteristics of those models, built with natural logarithms of the original data, through Ordinary Least Squares method (the software used was Wizard for MacOS), as regards three variables: the price fork in the retail market of electricity, the share of electricity in energy consumption, and the share of renewables in the output of electricity. Linear regression partly confirms the insights from studying Pearson correlation, and yet provides some new ones. As regards the overall explanatory power of those regressions, measured with the R^2 coefficient of determination, the apparent market imperfection in the retail prices of electricity comes as the best linearly explained one, with the share of electricity in energy consumption coming way after, and the share of renewables in electricity output having hardly any linear explanation at all, with an $R^2 = 0,133$. Another angle of approach to the overall explanatory power of those regressions is the magnitude of the constant term, combined with the t-significance of its correlation with the dependent variable. Variables which one could intuitively label as 'positive change', thus the share of electricity and the share of renewable sources, have their natural logarithms endowed with substantial, strongly correlated constant term. In other words, they display significant inertia regarding their correlates in the dataset. Conversely, the observable fork in retail prices of electricity, thus a disturbance to the market, has its natural logarithm coming with a constant term, which, whilst substantial in size, displays weak a t-significance. In the same linear model, numerous explanatory variables have their natural logarithms quite loosely connected to the explained variable, as judged by their t-statistics.

Table 2 - Linear regression of ln(Electricity % in total energy) on correlated variables, $R^2 = 0,429$

Variable	coefficient	std. error	t-statistic	p-value
ln(Renewables in electricity output %)	-0,059	0,014	-4,114	< 0,001
ln(ctfp)	0,235	0,067	3,526	< 0,001
ln(pl_con)	-4,268	1,366	-3,125	0,002
ln(pl_da)	5,983	0,887	6,745	< 0,001
ln(pl_c)	0,288	1,136	0,254	0,800
ln(pl_i)	1,192	0,436	2,738	0,007
ln(pl_g)	-0,301	0,356	-0,847	0,398
ln(pl_x)	-1,329	0,286	-4,647	< 0,001
ln(pl_n)	-1,589	0,226	-7,02	< 0,001
Constant	-1,893	0,092	-20,617	< 0,001

Table 3 Linear regression of ln(Renewables % in electricity) on correlated variables, $R^2 = 0,133$

variable	coefficient	std. error	t-statistic	p-value
ln(pl_da)	2,786	1,17	2,381	0,018
ln(pl_i)	3,867	1,497	2,584	0,010
ln(pl_g)	-1,216	0,582	-2,09	0,037
ln(pl_x)	-5,18	0,975	-5,312	< 0,001
ln(pl_n)	-2,878	1,034	-2,783	0,006
constant	-3,218	0,336	-9,566	< 0,001

Table 4 Linear regression of ln(Price fork in retail electricity) on correlated variables, $R^2 = 0,797$

Variable	coefficient	std. error	t-statistic	p-value
ln(Resident patent applications)	-0,21	0,326	-0,644	0,520
ln(patapp/popm in millions)	0,317	0,316	1,003	0,317
ln(pl_n)	-2,75	0,692	-3,973	< 0,001
ln(pl_m)	-2,609	0,859	-3,038	0,003
ln(pl_g)	-3,747	1,279	-2,93	0,004
ln(pl_i)	-0,517	1,469	-0,352	0,725
ln(pl_c)	-8,953	2,714	-3,298	0,001
ln(csh_g)	-6,648	1,628	-4,084	< 0,001
ln(csh_c)	-16,638	4,454	-3,736	< 0,001
ln(pl_gdpo)	24,562	5,574	4,406	< 0,001
ln(pl_da)	-8,157	9,418	-0,866	0,387
ln(pl_con)	0,72	7,152	0,101	0,920
ln(irr)	-1,077	0,216	-4,995	< 0,001
ln(rnna)	-0,009	0,413	-0,022	0,983
ln(rdana)	-3,944	2,875	-1,372	0,171
ln(rconna)	-0,351	2,342	-0,15	0,881
ln(rgdpna)	0,737	0,412	1,789	0,075
ln(ctfp)	1,607	0,379	4,234	< 0,001
ln(avh)	1,323	0,46	2,88	0,004

ln(cn)	-1,403	0,538	-2,609	0,010
ln(ck)	0,989	0,479	2,063	0,040
ln(Renewables in electricity output %)	0,026	0,036	0,735	0,463
ln(rgdpe)	-12,016	5,605	-2,144	0,033
ln(rgdpo)	-0,944	1,968	-0,48	0,632
ln(ccon)	21,687	6,971	3,111	0,002
ln(cda)	2,281	3,189	0,715	0,475
ln(cgdpe)	-6,626	6,89	-0,962	0,337
Constant	-17,569	10,82	-1,624	0,106

The results of applying the neural network

The dataset used in this research displays a lot of intriguing traits, possibly informative about underlying social change. The data looks as if a lot of white noise was there. Here comes the usefulness of a neural network. In most methods of data analysis, the researcher attempts to get rid of aleatory errors by decomposing them into patterned, predictable components. This is the idea behind the whole category of models based on stochastic processes. To the extent that quantitative socio-economic variables tell the story of a society, significant error means that we don't really understand what those people are doing. In neural networks error means learning. Observable error in optimizing a specific variable means one more step on the path of learning how to optimize it. The technical difference between other quantitative methods and a neural network is that the former treat all the errors observed at once, as one phenomenal occurrence, whilst neural networks build up a learning on sequenced errors.

Regarding the dataset described above, in the view of using a neural network as simulator of collective intelligence at work in an adaptive walk in rugged landscape, the general **hypothesis** formulated in the introduction is specifically rephrased as "**In the dataset at hand, i.e. in the European market of energy since 2008 through 2017, the share of renewable energy in the total output of electricity, the share of electricity in the total consumption of energy, and price imperfections in the retail market of electricity are instrumental to the optimization of other collective outcomes represented by the variables studied**".
The detailed results of processing the dataset described above with the neural network presented earlier in the section 'Method' are to find in the Excel workbook, accessible via the author's blog, under the link: https://discoversocialsciences.com/wp-content/uploads/2020/02/Comparison-of-Perceptrons-February-3rd-2020.xlsx . Here below, the most significant findings are presented and discussed.

When tested for Euclidean distance $\boldsymbol{E(X; S_i)}$ with equation (1), the 49 sets $\boldsymbol{S_i}$ created with the neural network, and pegged on the respective 49 variables, are all quite close to the source dataset $\boldsymbol{X}$. The furthest one, optimizing the variable RGDPO (Output-side real GDP at chained PPPs, in millions of 2011US$) as its output is at $\boldsymbol{E(X; S_i)}$ = 0,025864864 away from the set $\boldsymbol{X}$. By author's experience with the here-presented method, it is not far. The first provisional conclusion is that none of the 49 variables studied can be excluded as informative about a social outcome pursued by the collective intelligence supposedly at work in the dataset studied. Still, a hierarchy emerges. The social system represented by dataset $\boldsymbol{X}$ seems to be optimizing the price index of export transactions in the first place, or ***pl_x*** in the original database. The neural network pegged on this specific variable as expected output to optimize displayed a Euclidean distance of $\boldsymbol{E(X, S_{PL\_X}) = 0{,}002747526}$. Six other mutations $\boldsymbol{S_i}$ follow closely as for their

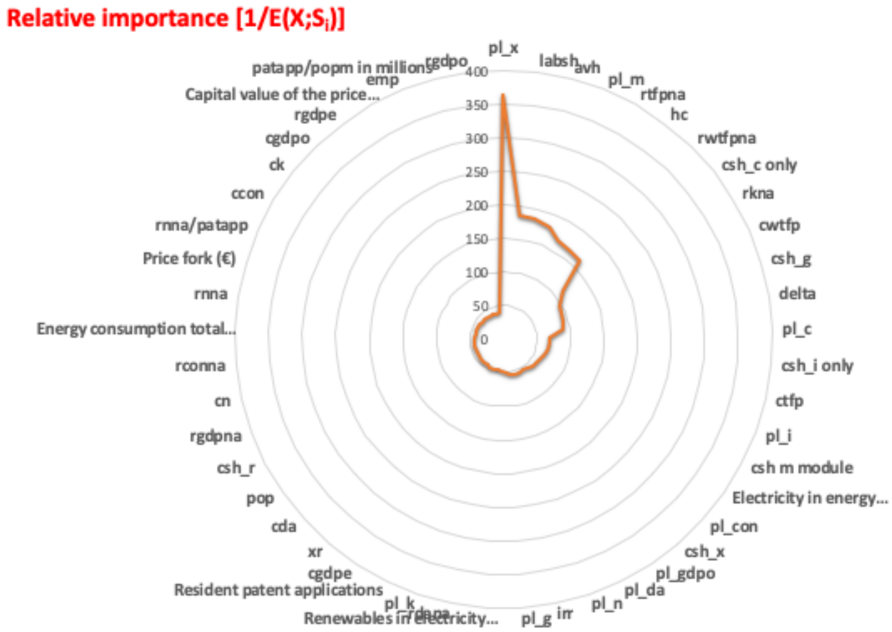
Euclidean similarity, pegged, respectively, on: share of labour in the national income ***E(X, S_{labsh}) = 0.005377882***, average number of hours worked per year per person ***E(X, S_{avh}) = 0.005384642***, price index in imports ***E(X, S_{pl_m}) = 0.005530757***, Total Factor Productivity (TFP) at constant national prices (2011=1) ***E(X, S_{rtfpna}) = 0.005966561***, human capital index, based on years of schooling and returns to education, ***E(X, S_{hc}) = 0.006115455***, and finally welfare-relevant TFP at constant national prices (2011=1), ***E(X, $S_{rwtfpna}$) = 0,006186732***.

Comparatively, neural-network-transformed sets ***S_i*** based on variables pertinent to the market of energy come with the following Euclidean distances:

a) *E(X; $S_{share\ of\ electricity\ in\ total\ energy}$) = 0,016424704*
b) *E(X; $S_{share\ of\ renewables\ in\ electricity}$) = 0,021189185*
c) *E(X; $S_{price\ fork\ regarding\ retail\ in\ electricity}$) = 0,023596012*
d) *E(X; $S_{capital\ value\ of\ the\ price\ fork}$) = 0,025135603*

After the rather piecemeal study of Euclidean distances, a synthetic picture can be informative. **Figure 1** below attempts to do it, with a presentational trick: inverted values of Euclidean distances, thus ***1/E(X;S_i)***, have been calculated as direct measures of the relative importance which the social system studied seems to associate with each individual variable as collective value to pursue. The general idea of this method is to show, figuratively, which exact order of hills is the collective intelligence climbing. Hence, the radar type of graph has been chosen, as its general look is similar to that of a compass. The compass clearly takes one direction, that of value added based on export prices, and on labour. The next question to highlight is the robustness of that result, and the first step in assessing it is the Euclidean distance between the source set ***X*** and its randomized counterpart ***X_R***. That distance, measured initially without transforming XR with the neural network, i.e. without any specific orientation, is ***E(X; X_R) = 0,0000000000000003172***. When transformed with the neural network along equations (2) – (5), and pegged on apparently the most relevant social outcome – the export price index pl_x – the randomized set ***X_R*** yields a clone ***S(X_R)$_{pl\_x}$***, Euclidean-distant from the source set ***X*** at ***E[X; S(X_R)$_{pl\_x}$] = 0,003733136***. The provisional conclusion is that the order of phenomenal occurrences in the set ***X*** does not have a significant influence on the outcomes of learning. The sets X and XR are closer to each other than to any set Si, and the same is true for the mutual distance between ***S_{PL_X}*** and ***S(X_R)$_{pl\_x}$***.

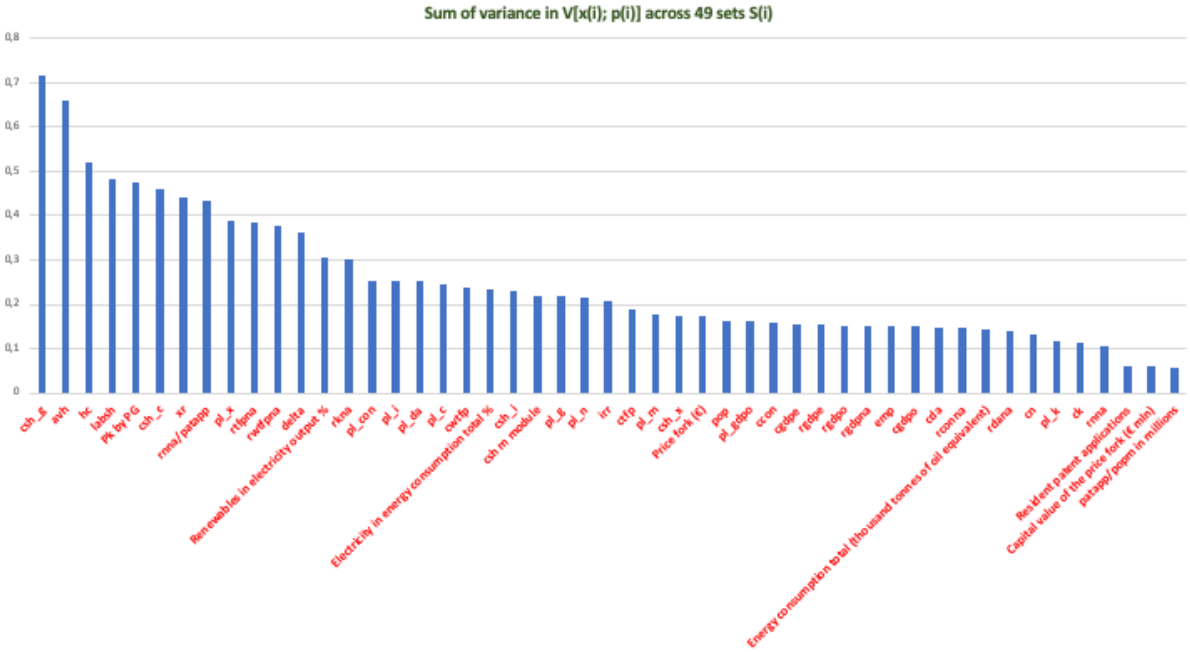
[FIGURE 1 Relative importance of variables in the dataset X as desired social outcomes (1/Euclidean distance from X)]



The next step - both for exploration and for assessment of robustness - is the analysis of variance in the local fitness functions $V[x_i(p_j)]$. The detailed results of that analysis are contained in the same Excel workbook as referenced above, available at: https://discoversocialsciences.com/wp-content/uploads/2020/02/Comparison-of-Perceptrons-February-3rd-2020.xlsx . The first observation as regards this specific metric is coherence: across 48 sets S_i out of the 49 generated with the neural network, variances in local fitness functions $V[x_i(p_j)]$ of all the 49 variables are quite even. Interestingly, only set S_i yields different variances, namely the one pegged on the coefficient of patent applications per 1 million people. On the whole, the neural network built of equations (2) – (5) seems to be robust for representing adaptive walk in rugged landscape, as regards the countries studied.

Across all the 49 sets S_i, variances in local fitness functions $V[x_i(p_j)]$ have been added up, for each variable x_i separately. This summation is supposed to represent the total capacity of each variable to enter into epistatic interactions with other variables, as the social system studied climbs different hills, i.e. pursues different outcomes to optimize. The results are visualized in Figure 2, below. The distribution of total variance is visibly more egalitarian than Pareto one. It is clearly not the case of '20% in the lot of variables doing 80% of epistatic work'. Still, a hierarchy emerges. The share of government expenditures in Gross National Income (csh_g) comes as the leading epistatic factor, closely followed by much the same variables, pertinent to the labour market, which appear to be among the leading outcomes pursued by the social system studied: number of hours worked per person per year (AVH), the index of human capital development (HC), and the share of labour in the Gross National Income (LABSH).

[FIGURE 2 Total variance in local fitness functions $V[x_i(p_j)]$ across all the 49 sets S_i]



Conclusion and final discussion

As we face climate change, it is useful to know which tangent are we collectively taking: how is our collective action coherent with the challenge at hand? Two goals are certainly important in that view: increasing the share of electricity in the overall consumption of energy and increasing the share of renewable sources in the generation of electricity. Human societies can develop tacit coordination, observable in the market of energy as well, which can possibly trigger evolutionary change in the form of adaptive walk in rugged landscape. This phenomenon, in turn, can be studied as a case of collective intelligence, where observable socio-economic variables are manifestations of the past, coordinated decisions. Empirical research presented in this article explores the hypothetical claim that development of electricity (to the detriment of direct burning of fossil fuels), and the development of renewable energy sources, in the economic context of Europe, are both instrumental to the optimization of other social outcomes, i.e. they are not explicitly pursued values of the society studied.

This article introduces a relatively novel method of studying quantitative, socio-economic data, with the use of a neural network, so as to discover patterns of evolutionary adaptation at the collective level, especially in the view of changing the energy base of human societies towards more sustainable ones. The methodological novelty consists in using the capacity of a neural network to produce many variations of itself, instead of exploiting exclusively its capacity to optimize. The theory of evolutionary adaptive walks in rugged landscape forms the theoretical base of the method presented. A tentative review of research on intelligent systems attempts to bridge between this evolutionary theory, and the application of neural networks for empirical discovery.

Two hierarchies of variables observed emerge from that empirical research: a hierarchy in collectively pursued goals, and a hierarchy in epistatic factors of evolutionary change. In both hierarchies, variables focused on in this research – the share of electricity in total consumption of energy and the share of renewable sources in the generation of electricity – come at distant places. They truly seem instrumental to social change reflected in other variables studied. The price index in exports (PL_X) comes as the chief collective goal pursued, and the share of public expenditures in the Gross National Income (CSH_G) appears as the main epistatic driver in that pursuit. These two have clear functional connection in the specific context of Europe. European countries largely trade with each other, and whatever they export out of EU is endowed with high value added. That high value added is largely powered with public subsidies, e.g. in the case of exports in agricultural goods.

Still, right after those top variables, phenomena observable through the lens of the empirical dataset present themselves under an interesting angle. Both in the hierarchy of collectively pursued outcomes, and in that of epistatic factors of change, three variables float very close to the top: the number of hours worked per person per year (AVH), the share of labour in the GNI (LABSH), and the indicator of human capital (HC). They seem to make an axis of social change: as input, they transform their epistatic interactions with other, so as to transform themselves as output variables. The economies of the 28 European countries under scrutiny, taken as one big social system, seem to be evolving along a path formed by the phenomena which underly the three variables in question: workstyles, compensation of work, and work-relevant education. In the precise case considered, i.e. 28 European countries between 2008 and 2017, the share of labour in the GNI had slightly fallen (from 55,8% to 54,8%), the human capital index had grown from 3.14 to 3.3, whilst the average number of hours worked per person per year had dropped gently from 1769,6 to 1714,11.

What connection between work and the labour market, on the one hand, and the ways we use energy, notably with the role of electricity, that of renewable energies, as well as with market imperfections in the retail sales of electricity, on the other hand? Many interpretations are possible, yet two seem quite obvious. Firstly, human work is work in interaction with technology, and the basket of technologies we use determines the ways we use energy. Secondly, work in itself is human effort, and that effort is functionally connected to the energy base of our society. The latest **World Development Report (WDR)** by World Bank **(World Bank 2019)** brings interesting observations as for the impact of technological change on the labour market. Apparently, at least so far, the fears of robots and digital technologies sweeping millions of jobs out of existence are unfounded. WDR 2019 brings evidence that not only don't those new technologies destroy jobs, but they also create whole new job categories and new sub-markets for human labour. Still, developing human capital is crucial: new jobs can appear, accompanying new technologies, when people acquire new skills. The most likely scenario for the global labour market is that, whilst new technologies do can create new jobs, people will have to adapt deeply in their lifestyles, including education, and cross-jobs mobility. The already proverbial 'uberization' of the labour market is a fact.

The impact of digital technologies upon the labour market can be expressed in an otherwise simple way, as correlation with two coefficients, namely that of number of hours worked per person per year, as well as the share of labour in the national income. The greater those coefficients, in the presence of technological change, the more 'job-making' this change is, and vice versa. Whilst unemployment rates obey pretty clear rules, the coefficient of hours worked per person per year is much more idiosyncratic across countries, both in terms of weeks worked, and that of hours worked per week **(**Fuchs-Schündeln et al. 2017). The coefficient of hours worked per person per year is correlated with technological change. More specifically, it seems being associated with the ratio of substitution between capital and labour. That ratio seems to be growing over time, and we seem to be facing a paradox: as technological change becomes faster, people work more per year. In general, between 1948 and 2009, the response of hours worked to technology shock has been varying in its shape, every 30 years, as if in a Kondratieff cycle (Cantore et al. 2017)**.**

The coefficient of hours worked per person per year is informative both about the technologies used by people working, and about the workstyles built around those technologies. Interestingly, that coefficient seems to be inversely correlated with income, still, the correlation is rather international than intranational. When developing countries are compared with the developed ones, the average adult in the former category works about 50% more per week than the average adult in the latter group. However, inside countries, the same type of correlation reverts, and one sees richer people work more than the relatively poorer ones (Bick et al. 2018).

Somewhat in the background of research on the strictly speaking coefficient of hours worked, another question arises: do we adapt our balance between workload and leisure to our expected consumption, or maybe we do something else, i.e. form a balance between consumption and savings on the grounds of what the local labour market imposes on us? Interestingly, both approaches may be quantitatively robust (Koo et al. 2013). Research focused on the impact of institutional changes, e.g. new environmental regulations, upon the labour market suggest that the latter is much more adaptable than in was assumed in the past, and has the capacity to offset the disappearance of jobs in some sectors by the creation of jobs in other sectors (Hafstead & Williams 2018).

Since David Ricardo, all the way through the works of Karl Marks, John Maynard Keynes, and those of Kuznets, economic sciences seem to be treating the labour market as easily transformable in response to an otherwise exogenous technological change. It is the assumption that technological change brings greater a productivity, and technology has the capacity to bend social structures. In this view, work means executing instructions coming from the management of business structures. In other words, human labour is supposed to be subservient and executive in relation to technological change. Still, the interaction between technology and society seems to be mutual, rather than unidirectional (Mumford 1964, McKenzie 1984, Kline and Pinch 1996; David 1990, Vincenti 1994). The relation between technological change and the labour market can be restated in the opposite direction. There is a body of literature, which perceives society as an organism, and social change is seen as complex metabolic adaptation of that organism. This channel of research is applied, for example, in order to apprehend energy efficiency of national economies. The so-called MuSIASEM model is an example of that approach, claiming that complex economic and technological change, including transformations in the labour market, can be seen as a collectively intelligent change towards optimal use of energy (see for example: Andreoni 2017 op. cit.; Velasco-Fernández et al 2018 op. cit.). Work can be seen as fundamental human activity, crucial for the management of energy in human societies. The amount of work we perform creates the need for a certain caloric intake, in the form of food, which, in turn, shapes the economic system around, so as to produce that food. This is a looped adaptation, as, on the long run, the system supposed to feed humans at work relies on this very work.

What if economic systems, inclusive of their technological change, optimized themselves so as to satisfy a certain workstyle? The thought seems incongruous, and yet Adam Smith noticed that division of labour, hence the way we work, shapes the way we structure our society. Can we hypothesise that technological change we are witnessing is, most of all, a collectively intelligent adaptation in the view of making a growing mass of humans work in ways they collectively like working? That would revert the Marxist logic, still, the report by World Bank, cited in the beginning of the article, allows such an intellectual adventure. On the path to clarify the concept, it is useful to define the meaning of collective intelligence.

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Appendix – List of variables in the source empirical set X

Table 5 – List of variables used in the empirical set X

Name of the variable	Explanatory note
Price fork P(H)- P(N)	residual difference between the price of electricity for household users [P(H)], and that for non-household users [P(N)] (€) ; source: author's, on the grounds of data providied by EUROSTAT
Capital value of the price fork (€ mln)	price fork P(H) - P(N) , multiplied by the quantity Q(E;H) of electricity consumed, in kWh, estimated for the population of household users (€ mln); source: author's, on the grounds of data provided by EUROSTAT
Energy consumption total (thousand tonnes of oil equivalent)	Entire population of users, households and non-household; source: EUROSTAT
Electricity in energy consumption total %	Entire population of users, households and non-household; source: EUROSTAT
Renewables in electricity output %	Share of renewable sources of energy in the total amount of energy consumed; source: World Bank
rgdpe	Expenditure-side real GDP at chained PPPs (in mil. 2011US$); source: Penn Tables 9.1
rgdpo	Output-side real GDP at chained PPPs (in mil. 2011US$); source: Penn Tables 9.1
pop	Population (in millions); source: Penn Tables 9.1
emp	Number of persons engaged (in millions); source: Penn Tables 9.1
avh	Average annual hours worked by persons engaged; source: Penn Tables 9.1
hc	Human capital index, based on years of schooling and returns to education; see Human capital in PWT9.; source: Penn Tables 9.1
ccon	Real consumption of households and government, at current PPPs (in mil. 2011US$); source: Penn Tables 9.1
cda	Real domestic absorption, (real consumption plus investment), at current PPPs (in mil. 2011US$); source: Penn Tables 9.1
cgdpe	Expenditure-side real GDP at current PPPs (in mil. 2011US$); source: Penn Tables 9.1
cgdpo	Output-side real GDP at current PPPs (in mil. 2011US$); source: Penn Tables 9.1
cn	Capital stock at current PPPs (in mil. 2011US$); source: Penn Tables 9.1
ck	Capital services levels at current PPPs (USA=1); source: Penn Tables 9.1
ctfp	TFP level at current PPPs (USA=1); source: Penn Tables 9.1
cwtfp	Welfare-relevant TFP levels at current PPPs (USA=1); source: Penn Tables 9.1
rgdpna	Real GDP at constant 2011 national prices (in mil. 2011US$); source: Penn Tables 9.1
rconna	Real consumption at constant 2011 national prices (in mil. 2011US$); source: Penn Tables 9.1

rdana	Real domestic absorption at constant 2011 national prices (in mil. 2011US$); source: Penn Tables 9.1
rnna	Capital stock at constant 2011 national prices (in mil. 2011US$); source: Penn Tables 9.1
rkna	Capital services at constant 2011 national prices (2011=1); source: Penn Tables 9.1
rtfpna	TFP at constant national prices (2011=1); source: Penn Tables 9.1
rwtfpna	Welfare-relevant TFP at constant national prices (2011=1); source: Penn Tables 9.1
labsh	Share of labour compensation in GDP at current national prices; source: Penn Tables 9.1
irr	Real internal rate of return; source: Penn Tables 9.1
delta	Average depreciation rate of the capital stock; source: Penn Tables 9.1
xr	Exchange rate, national currency/USD (market+estimated); source: Penn Tables 9.1
pl_con	Price level of CCON (PPP/XR), price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_da	Price level of CDA (PPP/XR), price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_gdpo	Price level of CGDPo (PPP/XR), price level of USA GDPo in 2011=1; source: Penn Tables 9.1
csh_c	Share of household consumption at current PPPs; source: Penn Tables 9.1
csh_i	Share of gross capital formation at current PPPs; source: Penn Tables 9.1
csh_g	Share of government consumption at current PPPs; source: Penn Tables 9.1
csh_x	Share of merchandise exports at current PPPs; source: Penn Tables 9.1
csh_m	Share of merchandise imports at current PPPs; source: Penn Tables 9.1
csh_r	Share of residual trade and GDP statistical discrepancy at current PPPs; source: Penn Tables 9.1
pl_c	Price level of household consumption, price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_i	Price level of capital formation, price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_g	Price level of government consumption, price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_x	Price level of exports, price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_m	Price level of imports, price level of USA GDPo in 2011=1; source: Penn Tables 9.1
pl_n	Price level of the capital stock, price level of USA in 2011=1; source: Penn Tables 9.1
pl_k	Price level of the capital services, price level of USA=1; source: Penn Tables 9.1

Resident patent applications	source: World Bank
rnna/patapp	Capital stock per 1 resident patent application, constant 2011 national prices (in mil. 2011US$); source: author's, based on data from World Bank, and Penn Tables 9.1.
patapp/pop in millions	Average number of resident patent applications per 1 mln people; source: author's, based on data from World Bank, and Penn Tables 9.1.