Energy efficiency as manifestation of collective intelligence in human societies

Author: *Krzysztof Wasniewski, PhD*
Affiliation: *The Andrzej Frycz Modrzewski Krakow University, Department of Management, Krakow, Poland*

Abstract

This article attempts to assess the real capacity of national economies to optimize their energy efficiency, measured as real output per unit of energy consumed. National economies are assumed to be collective intelligences, striving to optimize a set of values, including energy efficiency. A set of 59 countries has been studied in this respect over the period 1990 – 2014, with the use of a multi-layer perceptron mimicking their collective intelligence, expressed in 14 quantitative variables. The results obtained suggest that economies studied optimize the proportion between their R&D effort and their fixed capital in the first place, then they strive to optimize their sheer economic and demographic scale, and only after these values, they optimize their energy efficiency. Further theoretical interpretation allows guessing the presence of an evolutionary function of sexual selection between social sub-structures.

Keywords: energy, energy efficiency, collective intelligence, artificial intelligence, technological change

Introduction

Since 2012, the global economy has been going through an unprecedentedly long period of expansion in real output[1]. Whilst the obvious question is “When will it crash?”, it is interesting to investigate the correlates of this phenomenon in the sector of energy. In other terms, are we, as a civilisation more energy-efficient as we get (temporarily) much more predictable in terms of economic growth? The very roots of this question are to find in the fundamental mechanics of our civilisation. We, humans, are generally good at transforming energy. 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)

When we talk about energy efficiency of the human civilisation, it is useful to investigate the way we consume energy. In this article, the question is being tackled by observing the pace of growth in energy efficiency, defined as GDP per unit of energy use (https://data.worldbank.org/indicator/EG.GDP.PUSE.KO.PP.KD?view=chart). The amount of value added we can generate out of a given set of production factors, when using one unit of energy, is an interesting metric. It shows energy efficiency as such, and, in the same time, the relative complexity of the technological basket we use. As stressed, for example, by Moreau and Vuille (2018), when studying energy intensity, we need to keep in mind the threefold distinction between: a) direct consumption of energy b) transport c) energy embodied in goods and services.

One of the really deep questions one can ask about the energy intensity of our culture is to what extent it is being shaped by short-term economic fluctuations. Ziaei (2018) proved empirically that observable changes in energy intensity of the U.S. economy are substantial, in response to changes in monetary policy. There is a correlation between the way that financial markets work and the consumption of energy. If the relative increase in energy consumption is greater than the pace of economic growth, GDP created with one unit of energy decreases, and vice versa. There is also a mechanism of reaction of the energy sector to public policies. In other words, some public policies have significant impact on the energy efficiency of the whole economy. Different sectors of the economy respond with different intensity, as for their consumption of energy, to public policies and to changes in financial markets. We can assume that a distinct sector of the economy corresponds to a distinct basket of technologies, and a distinct institutional outset.

Faisal et al. (2017) found a long-run correlation between the consumption of energy and real output of the economy, studying the case of Belgium. Moreover, the same authors found significant causality from real output to energy consumption, and that causality seems to be uni-directional, without any significant, reciprocal loop.

Energy efficiency of national economies, as measured with the coefficient of GDP per unit of energy (e.g. per kg of oil equivalent), should take into account that any given market is a mix of goods – products and services – which generate aggregate output. Any combination “GDP <> energy use” is a combination of product markets, as well as technologies (Heun et al. 2018). There is quite a fruitful path of research, which assumes that aggregate use of energy in an economy can be approached in a biological way, as a metabolic process. The MuSIASEM methodological framework seems to be promising in this respect (e.g. Andreoni 2017). This leads to a further question: can changes in the aggregate use of energy be considered as adaptive changes in an organism, or in generations of organisms? In another development regarding the

[1] https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

MuSIASEM framework, Velasco-Fernández et al (2018) remind that real output per unit of energy consumption can increase, on a given basis of energy supply, through factors other than technological change towards greater efficiency in energy use. This leads to investigating the very nature of technological change at the aggregate level. Is aggregate technological change made only of engineering improvements at the microeconomic level, or maybe the financial reshuffling of the economic system counts, too, as adaptive technological change?

The MuSIASEM methodology stresses the fact that international trade, and its accompanying financial institutions, allow some countries to externalise industrial production, thus, apparently, to decarbonise their economies. Still, the industrial output they need takes place, just somewhere else.

From the methodological point of view, the MuSIASEM approach explores the compound nature of energy efficiency measured as GDP per unit of energy consumption. Energy intensity can be understood at least at two distinct levels: aggregate and sectoral. At the aggregate level, all the methodological caveats make the « GDP per kg of oil equivalent » just a comparative metric, devoid of much technological meaning. At the sectoral level, we get closer to technology strictly spoken.

There is empirical evidence that at the sectoral level, the consumption of energy per unit of aggregate output tends to: a) converge across different entities (regions, entrepreneurs etc.) b) tends to decrease (see for example: Yu et al. 2012).

There is also empirical evidence that general aging of the population is associated with a lower energy intensity, and urbanization has an opposite effect, i.e. it is positively correlated with energy intensity (Liu et al. 2017)

It is important to understand, how and to what extent public policies can influence the energy efficiency at the macroeconomic scale. These policies can either address directly the issue of thermodynamic efficiency of the economy, or just aim at offshoring the most energy – intensive activities. Hardt et al. (2018) study, in this respect, the case of United Kingdom, where each percentage of growth in real output has been accompanied, those last years, by a 0,57% reduction in energy consumption per capita.

There is grounds for claiming that increasing energy efficiency of national economies matters more for combatting climate change that the strictly spoken transition towards renewable energies (Weng, Zhang 2017). Still, other research suggest that the transition towards renewable energies has an indirectly positive impact upon the overall energy efficiency: economies that make a relatively quick transition towards renewables seem to associate that shift with better efficiency in using energy for creating real output (Akalpler, Shingil 2017).

It is to keep in mind that the energy efficiency of national economies has two layers, namely the efficiency of producing energy in itself, as distinct from the usage we make of the so-obtained net energy. This is the concept of Energy Return on Energy Invested (EROI), (see: Odum 1971; Hall 1972). Changes in energy efficiency can occur on both levels, and in this respect, the transition towards renewable sources of energy seems to bring more energy efficiency in that first layer, i.e. in the extraction of energy strictly spoken, as compared with fossil fuels. The problematically slow growth in energy efficiency could be coming precisely from the de-facto decreasing efficiency of transformation in fossil fuels (Sole et al. 2018).

Technology and social structures are mutually entangled (Mumford 1964, McKenzie 1984, Kline and Pinch 1996; David 1990, Vincenti 1994; Mahoney 1988; Ceruzzi 2005). An excellent, recent piece of research by Taalbi (2017) attempts a systematic, quantitative investigation of that entanglement.

The data published by the World Bank regarding energy use per capita in kg of oil equivalent (OEPC) (https://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE) allows an interesting insight, when combined with structural information provided by the International Energy Agency (https://www.iea.org). As one ranks countries regarding their energy use per capita, the

resulting hierarchy is, in the same time, a hierarchy in the broadly spoken socio-economic development. Countries displaying less than 200 kg of oil equivalent per capita are, in the same time, barely structured as economies, with little or no industry and transport infrastructure, with quasi-inexistent institutional orders, and with very limited access to electricity at the level of households and small businesses. In the class comprised between 200 kg OEPC and approximately 600 ÷ 650 kg OEPC, one can observe countries displaying progressively more and more development in their markets and infrastructures, whilst remaining quite imbalanced in their institutional sphere. Past the mark of 650 OEPC, stable institutions are observable. Interestingly, the officially recognised threshold of « middle income », as macroeconomic attribute of whole nations, seems corresponding to a threshold in energy use around 1 500 kg OEPC. The neighbourhood of those 1 500 kg OEPC looks like the transition zone between developing economies, and the emerging ones. This is the transition towards really stable markets, accompanied by well-structured industrial networks, as well as truly stable public sectors. Finally, as income per capita starts qualifying a country into the class of « developed economies », that country is most likely to pass another mark of energy consumption, that of 3000 kg OEPC. This stylized observation of how energy consumption is linked to social structures is partly corroborated by other research, e.g. that regarding social equality in the access to energy (see for example: Luan, Chen 2018)
The nexus of energy use per capita, on the one hand, and institutions on the other hand, has even found a general designation in recent literature: "energy justice". A cursory review of that literature demonstrates the depth of emotional entanglement between energy and social structures: it seems to be more about the connection between energy and self-awareness of societies than about anything else (see for example: Fuller, McCauley 2016; Broto et al. 2018). The difficulty in getting rid of emotionally grounded stereotypes in this path of research might have its roots in the fact that we can hardly understand what energy really is, and attempts at this understanding send us to the very foundations of our understanding as for what reality is (Coelho 2009; McKagan et al. 2012; Frontali 2014). Recent research, conducted from the point of view of management science reveal just as recent an emergence of new, virtually unprecedented, institutional patterns in the sourcing and the use of energy. A good example of that institutional change is to find in the new role of cities as active players in the design and implementation of technologies and infrastructures critical for energy efficiency (see for example: Geels et al. 2016; Heiskanen et al. 2018; Matschoss, Heiskanen 2018).

Changes observable in the global economy, with respect to energy efficiency measured as GDP per unit of energy consumed, are interestingly accompanied by those in the supply of money, urbanization, as well as the shift towards renewable energies. Years 2008 – 2010, which marked, with a deep global recession, the passage towards currently experienced, record-long and record-calm period of economic growth, displayed a few other interesting transitions. In 2008, the supply of broad money in the global economy exceeded, for the first documented time, 100% of the global GDP, and that coefficient of monetization (i.e. the opposite of the velocity of money) has been growing ever since (World Bank 2018). Similarly, the coefficient of urbanization, i.e. the share of urban population in the global total, exceeded 50% in 2008, and has kept growing since (World Bank 2018). Even more intriguingly, the global financial crisis of 2007 – 2009 took place exactly when the global share of renewable energies in the total consumption of energy was hitting a trough, below 17%, and as the global recovery started in 2010, that coefficient started swelling as well, and has been displaying good growth since then[2]. Besides, empirical data indicates that since 2008, the share of aggregate amortization (of fixed assets) in the global GDP has been consistently growing, after having passed the cap of 15%

[2] https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS last accessed November 25th, 2018

(Feenstra et al. 2015). Some sort of para-organic pattern emerges out of those observations, where energy efficiency of the global economy is being achieved through more intense a pace of technological change, in the presence of money acting as a hormone, catabolizing real output and fixed assets, whilst anabolizing new generations of technologies.

It is worth noticing that energy efficiency, as a coefficient, can be factorised into component, meaningful coefficients: GDP/energy consumed = (GDP per capita) / (Energy consumed per capita). Seen under this angle, the metric "GDP/Energy consumed" can be interpreted as local equilibrium rather than efficiency strictly spoken. This, in turn, allows guessing some sort of collective intelligence at work, which is quite a logical extension of the metabolic approach shown in the MuSIASEM methodology. **The baseline working hypothesis of this article is that energy efficiency of national economies is a local equilibrium, achieved indirectly, though not purposefully.**

In social sciences, quantitative variables frequently take the form of coefficients, e.g. density of population, energy efficiency, GDP per capita etc. Some of those coefficients bear the marks of local equilibriums. Density of population is probably the most obvious example: it is a local balance between the headcount of population, its spatial movement, and resources available in the given territory. Some other coefficients, such as energy efficiency measured as the value of real output per unit of energy consumed, are somehow puzzling: they can be interpreted both as efficiencies strictly spoken (i.e. as functional attributes of a process subject to optimization), and as local equilibriums. The same coefficients are socially important, and their optimization is an important challenge for whole societies. As we ask, whether at all and to what extent can we optimize, as a society, a given proportion, another question emerges: 'So far, as a society, have we been optimizing this proportion at all? What other types of social optimization is this one coherent with?'. In other words, when we ask if we can collectively learn something, discovering whether somebody somewhere had already learnt something similar is a useful insight.

Besides this fundamental problem, there is another one, more analytical. When we construe an econometric model, or, even more broadly, a sociometric one, distinction between the explained variable, on the one hand, and the explanatory variables, on the other hand, is largely arbitrary. The distinction can be sharpened by using, for example, time-lagged values in the variables deemed explanatory. Still, arbitrariness remains.

Recent advances in Artificial Intelligence result in more and more frequent application of neural networks in social research, as an alternative to classical, regression-based models. From the cognitive point of view, the essential difference between a neural network and stochastic regression is the utilisation of residual errors in estimation. In regression, the predictive function minimizes the average error, i.e. all the local errors are computed, and an error-minimizing function is derived. In neural networks, each consecutive local error is utilised as material for learning as regards the next empirical observation. Neural networks allow deepening the study of equilibrium states in social sciences, by extending the concept of equilibrium into a broader assumption of collective intelligence being at work. Moving equilibriums can be studied as moving homeostasis. The general assumption underlying this method is that empirical values observable in any quantitative variable used to describe a society, such as, for example, GDP per capita, can be considered as the cumulative outcome of past collective actions and decisions. Consequently, mathematically verifiable, logical links between those variables are informative about correlations between the actions and decisions in question.

The so-called ‘swarm theory’ (Stradner et al. 2013) provides a possible theoretical basis for using neural networks as viable representations of collective intelligence in human societies. The swarm theory argues that collective intelligence manifests as changing cohesion between individual patterns of behaviour. Three typical levels of cohesion are distinguished: static coupling (the tightest one), dynamic correlated coupling, and dynamic random coupling (the loosest one). The relative strength of coupling between actions and decisions in a society is scalable and measurable as a fitness function, i.e. as the Euclidean distance between the corresponding numerical vectors (de Vincenzo et al. 2018). If a set of empirical data, pertinent to social phenomena, and treated by a neural network, displays visible changes in the value of its general fitness function, it can be assumed that the data in question represents collective intelligence.

Neural networks are made for optimizing. Input variables are being experimented with in order to find such their combination, which yields the greatest accuracy in driving the output variable towards desired values. This property of neural networks can be used in order to discover, which social phenomena, from among those measured with quantitative variables we study, are really the desired outcome of collective intelligence. In other words, a neural network can be used to discover teleological orientations in collective intelligence of human societies. For the same set of empirical data, informative about the state of society, and made of n variables, we can build many neural networks endowed with the same logical structure, and yet differing in the classification of variables into respectively, the output variable subject to optimization, and input variables, instrumental in that view. The values produced by each such network can be compared with the source empirical data, and, logically, the neural network that yields the greatest similarity to the latter can be treated as its best approximation. The output variable of that most similar neural network can be considered as the most likely to be the value optimized by the society under scrutiny.

The basic theoretical model

In this paper, a mixed procedure of research is presented, combining the classical econometric approach with the assumption of collective intelligence, and the use of neural networks. A set of quantitative variables has been selected, on the grounds of the literature cited in earlier paragraphs, as well as in accord with the author’s own, previous research (Wasniewski 2017a[3], Wasniewski 2017b[4]). It is further assumed that energy efficiency of national economies significantly depends on their strictly structural characteristics, i.e. by proportions between flows and balances in four main fields: the pace of technological change, the monetary system, the relative shift towards renewable energies, and the degree of urbanization. The pace of technological change is assumed to be observable as the proportion between aggregate amortization of fixed assets, and the real output of the economy. This structural coefficient, possible to express as a strict fraction, reflects the percentage of proceedings from real output that need to be reallocated into the maintenance of technological competitiveness. As regards the monetary system, the essential proportion referred to in the model is that between the aggregate supply of money, and real output.

[3] Wasniewski, K., (2017), Financial Equilibrium in the Presence of Technological Change, Journal of Economics Library, Volume 4 (2), June 20, s. 160 – 171, KSP Journals, Turkey, 2017
[4] Wasniewski, K., (2017), Technological change as intelligent, energy-maximizing adaptation, Journal of Economic and Social Thought, Volume 4 September 3, 263-276, Turkey, 2017

It is also assumed, consistently with theoretical remarks in the introduction, that energy efficiency is connected to relative poverty, as well as to the food base, which the given society has at its disposal. Thus, a theoretical variable of food intake per capita is included in the model. A residual constant of energy efficiency is supposed to be manifest in the presence of these structural factors. Equation (1) sums up this basic approach.

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + a_5\frac{F}{N} + b \qquad (1)$$

… where $\frac{Q}{E}$ is the coefficient of GDP (real output) per unit of energy consumed, $\frac{A}{Q}$ represents the ratio of aggregate amortization in fixed assets denominated in units of real output, the ratio $\frac{M}{Q}$ represents the share of money supply in the aggregate output (i.e. the opposite of the velocity of money) , $\frac{RE}{E}$ is the share of renewable energies in the final consumption of energy, $\frac{UN}{N}$ stands for the share of urban population in the total population, and $\frac{F}{N}$ represents food intake per capita.

The basic model has two mutations, corresponding to different types of scale factors. The type labelled further as 'weak scale factors' encompasses variables, which are coefficients of intensity, i.e. proportions denominated in absolute amounts instead of being denominated as fractions strictly spoken. They are: a) the coefficient of the number of domestic patent applications per 1000 000 inhabitants ($\frac{PatApp}{N}$) b) the coefficient of final energy consumption per capita ($\frac{E}{N}$) and c) the coefficient of real output per capita ($\frac{Q}{N}$) . Equation (2) represents formally this mutation of the basic model.

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + a_5\frac{F}{N} + a_6\frac{PatApp}{N} + a_7\frac{E}{N} + a_8\frac{Q}{N} + b \qquad (2)$$

The model containing weak scale factors reflects the general assumption that the more intense are the corresponding processes – patentable research, final consumption of energy and production of real output – in relation to the headcount of the population, the greater is the energy efficiency of the national economy. Besides, the weak scale factors are supposed to compensate distortions observable in the empirical distribution of structural variables $\frac{M}{Q}$ and $\frac{RE}{E}$ **.** The $\frac{M}{Q}$ tends to vary strongly in the cross-sectional dimension, without clear connection with the efficiency of technological base observable in a given country. The share of renewable energies in the overall energy consumption ($\frac{RE}{E}$) is subject to a distortion due to the formal definition of renewables. Biofuels are technically categorized as renewable sources of energy, and they make a substantial share of energy-sourcing in the poorest countries of the globe, yet that local, strong reliance on the burning of vegetal remains is not a proof of technological advancement. On the contrary, these are the least developed technological environments.

Another mutation of the basic model, containing the so-called strong scale factors, aims at capturing the impact of the sheer scale in national economies upon their respective energy efficiencies. Population (N) and real output (Q) are introduced into the basic model, supplanting the previously mentioned intensities, as shown in equation (3).

$$\frac{Q}{E} = a_1\frac{A}{Q} + a_2\frac{M}{Q} + a_3\frac{RE}{E} + a_4\frac{UN}{N} + a_8 N + a_9 Q + b \qquad (3)$$

For the purposes of research presented further below, consistently with earlier remarks, it is assumed that the logical structure of equations (1) – (3) is arbitrary, i.e. energy efficiency could be moved to their respective right side just as well, and replaced, on the left side, with another from among those variables.

The dataset and the neural network used to study it

A compound database has been created for the purposes of this research, covering the period since 1990 through 2014, as regards **59 countries**. Penn Tables 9.0 (Feenstra et al. 2015[5]) have been used for measuring the empirical values of real output, population, and that of aggregate amortization of fixed assets. A pooled dataset of m = 1228 country-year has been created. Data regarding energy efficiency, the share of renewables in the final consumption of energy, as well as that regarding money supply and R&D activity has been sourced from the database publicly available with the World Bank[6]. Each national society is represented by the same **set of 12 variables**: i) GDP per kg of oil equivalent in energy consumed (the outcome variable), ii) fixed assets per one patent application, iii) aggregate depreciation of fixed assets as % of the GDP, iv) number of resident patent applications per 1 million inhabitants, v) supply of broad money as % of the GDP, vi) energy use per capita, vii) depth of food deficit per capita, viii) % of renewables in the total consumption of energy, ix) % of urban population in total population, x) GDP and xi) population as scale factors, and xii) GDP per capita.

Regarding the variable of chief interest in this article, i.e. energy efficiency, the dataset used in this research is more energy efficient that the average disclosed by the World Bank. In 2014, the latter yielded 8,359 USD PPP per 1 kg of oil equivalent. The dataset used in this research yields 10,755 USD PPP. The mean energy efficiency over all the years observed is 8,7243.

The logical structure of the multi-layer perceptron (MLP) used in the here-presented research attempts to represent as accurately as possible the way a real collective intelligence works: theoretical representativeness is the chief concern, with speed and precision of learning being of lesser importance. The neural network consists of four distinct types of mathematical functions, corresponding to four distinct cognitive processes: perception of external information, auto-perception, neural activation, and forward feeding of results for further learning.

The layer of perception standardizes the source data. ***X*** represents the original set of empirical data, consisting of $\boldsymbol{n = 12}$ variables $\boldsymbol{x: X = \{x_1, x_2, \dots, x_{12}\}}$. Each of these variables can be used

[5] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt

[6] https://data.worldbank.org last accessed November 25th, 2018

either as one of input variables, or as the output one. Besides being structured into variables, ***X*** is structured into $m = 1228$ phenomenal occurrences '***o***', so as ***X = {o(1), o(2),…, o(1228)}***, and each ***j***-th phenomenal occurrence contains the local values of variables observed: $o(j) = \{x_1(j), x_2(j), \ldots, x_{12}(j)\}$, i.e. each "country – year" observation is a phenomenal occurrence ***o(j)***. ***Z*** represents the standardized set of empirical data, transformed from ***X*** via a function of perception ***fp(X)***, **where** $z_1 = fp(x_1)$, $z_2 = fp(x_2)$, …, $z_{12} = fp(12)$; ***Z*** is structured into $m = 1228$ phenomenal occurrences just as ***X*** is. Thus, $z_1(1)$ is the standardized value of variable x_1 in the phenomenal occurrence ***1*** etc. In the method such as it is presented here, it is assumed that the order of phenomenal occurrences is fixed. It corresponds to the assumption that a society, as collective intelligence, deals with an already given order of events to learn from.

Usually, standardization is not considered something that a neural network does in the strict sense of the term: the data simply should be fed into the network in standardized form. Still, standardization in itself is part of intelligent perception. In the here-presented research two types of standardization ***fp(X)*** have been used: standardization over maxima and that under the curve of cumulative Poisson distribution. The former represents linear perception, with stimuli being perceived on a linear scale of their relative strength. The latter reflects a collective intelligence which distinguishes sharply between the important stimuli and the unimportant ones.

The perceptron starts learning with the first phenomenal occurrence ***o(1)*** in the set ***Z***. Two operations are being carried out: neural activation and observation of the fitness function. $V[z_i(j)]$ stands for local value of the fitness function ***V*** in variable x_i (or ***y***), in the phenomenal occurrence ***j***; $V[z_i(j)]$ is calculated as the mean local Euclidean distance of $z_i(j)$ from other variables in the given ***j***-th phenomenal occurrence, as in equation (4) below.

$$V[z_i(j)] = \frac{\sum_{i=1}^{12} \sum_{k=1}^{12-1} \sqrt{[z_i(j) - z_k(j)]^2}}{12} \qquad (4)$$

$V[Z(j)]$ is the general fitness function of the set ***Z*** in the ***j***-th phenomenal occurrence, calculated as the mean value of $V[z_i(j)]$, as in equation (5).

$$V[Z(j)] = \frac{\sum_{i=1}^{12} V[z_i(j)]}{12} \qquad (5)$$

Neural activation occurs by feeding data ***Z(1)*** into the neural activation function ***g(1)***, used in the perceptron for estimating the value of output variable ***y*** in the phenomenal occurrence ***1***. In the original application of this method, the author used the function of hyperbolic tangent, or $g(j) = \frac{e^{2h}-1}{e^{2h}+1}$. Note that other activation functions (i.e. other than hyperbolic tangent) can be used; the key is the meaningfulness of results yielded by the perceptron. The variable ***h*** in ***Z(1)*** is calculated as $h = \sum_{i=1}^{12} z_i * w$, where ***w*** is a random weight $0 > w > 1$.

For each consecutive phenomenal occurrence used to teach the perceptron, local error of estimation is computed $e_y(j)$, as in equation (6). The factor $g'(j)$ is the first derivative of the activation function ***g(j)***. The idea behind adding it to the estimation of local error is that errors matter by their sheer magnitude as well as by the relative steepness of the neural activation function in the given phenomenal occurrence ***o(j)***.

$$e_y(j) = [g(j) - y] * g'(j) \quad (6)$$

The first round of learning with data, i.e. the perception, processing, estimation of coherence and that of accuracy yield two values: the vector of variable-specific local fitness functions ***V[Z(1)]***, and the local error ***e(1)***. The perceptron learns on its capacity to estimate the output variable 'y', and on the mutual coherence (Euclidean distance) of input variables. The underlying theoretical assumption is that collective intelligence attempts to achieve some outcomes and evaluates its own capacity to do it (that's why governments fall when they fail on key economic promises, for example), as well as its own coherence. The last assumption means that any culture learns and optimizes within a repertoire of moves coherent with the given set of social norms, e.g. changes in the healthcare system usually mean incremental change in public spending rather that brutal swing from 100% public funding to 100% private.

In the second round of learning, as well as in any consecutive one, thus when processing data ***Z(2) ≥ Z(j) ≥ Z(1228)***, the logical structure changes slightly. The parameter h of the neural activation function g(j) incorporates both the error generated in the previous round of learning, and the values of local fitness functions in the same preceding round, as in equation (7). Besides incorporating the lesson from previous rounds, the perceptron keeps experimenting with random weights $w(z_i)$, which, in turn, reflects the innovative component of collective intelligence.

$$h(2 \leq j \leq 1228) = \sum_{i=1}^{12} [z_i + e_y(j-1)] * w * V[z_i(j-1)] \qquad (7)$$

The procedure proposed in this method includes a formal check of intelligence, which, by the author's experience, is really a formality. The series of ***m = 1228*** general fitness functions ***V[Z(j)]***, as well as the series of ***m = 1228*** errors ***e(j)*** must both be non-monotonous. In other words, there must be demonstrable adjustment.

The set ***X*** of empirical observations, structured into ***m = 1228*** phenomenal occurrences and ***n = 12*** variables, treated with the neural network under two alternative methods of standardization – over local maxima and under cumulative Poisson curve - generates 24 transformed sets $S_1, S_2, \dots, S_{24}$ of values. Each set S_l can be compared as for its similarity to the original set ***X***. In the set ***X***, each variable x_i yields a mean value $avg(X;x_i)$ over ***m = 1228*** phenomenal occurrences. In the same manner, each variable x_i in each set S_l is endowed with a mean value $avg(S_l;x_i)$. Both the mean values value $avg(X;x_i)$ and the value $avg(S_l;x_i)$ are vectors, characteristic for their respective sets. Each set S_l can be compared to the set ***X*** as for the Euclidean distance $E(X;S_l)$ between these vectors, as in equation (8). Among the ***24*** sets S_l generated from the set ***X***, the set S_l endowed with the smaller Euclidean distance $min[E(X;S_l)]$ is the most similar to ***X***. Consequently, we can assume that the output variable of this specific set S_i is the most likely value optimized by the society represented in the original empirical set ***X***. Other sets S_l, endowed with higher $E(X;S_l)$ are, respectively, less and less likely representations of values pursued by the society studied.

$$E(X;S_l) = \sqrt{\sum_{l=1}^{24} \left[\frac{avg(S_l;x_i)}{avg(X;x_i)}\right]^2} \qquad (8)$$

1 Results

The neural network used for the purpose of the here-presented research in this article generates 12 distinct simulations, corresponding to the twelve sets $\boldsymbol{S_l}$, as referred to in the body text of the article as those based on linear standardization over local maxima. In the Appendix, at the end of this article, the reader can find a list of links to Excel spreadsheets that correspond to those sets, under the general heading 'List of accessory Excel files'. These files are available in the repository of the author's scientific blog. Inside each of them, the reader can find, among other things, the formal proof of intelligence, in the form of non-monotonous graphs of error, and those of general fitness functions. Besides, the Appendix contains two large tables with synthetic results, based mostly on equation (8). Here, in this section, the most significant results are discussed. The readers are welcome to study all the accessory material.

Generally, alternative sets $\boldsymbol{S_l}$ that the neural network yields under linear standardization over local maxima are much more similar, in the lines of equation (8), to the original set X than those generated with data standardized probabilistically under the cumulative Poisson curve. Table 1, in the Appendix, contains a detailed specification of Euclidean distances calculated conformingly to equation (8). Among the alternative sets generated under linear standardization over local maxima, the one optimizing the coefficient of fixed assets per 1 resident patent application wins, hands down, the contest of Euclidean similarity. Its Euclidean distance $\boldsymbol{E(X; S_l)}$ is 0,24, which is at least one order of magnitude less than any other set $\boldsymbol{S_l}$ generated under the same conditions of standardization in source data. The collective intelligence represented by empirical data used for this research seems to be optimizing the proportion between productive investment, and innovation, more than anything else. The question arises, where is energy efficiency placed in the hierarchy of values optimized by this collective intelligence? It seems to come in the fifth place. This precise collective intelligence, right after striving to optimize the coefficient of fixed assets per 1 patent application, optimizes, respectively in order of importance, the values of: resident patent applications per 1 mln people, GDP (demand side), and population. It seems to be a technology-and-scale-oriented collective intelligence.

As we factorise the coefficient of energy efficiency into, respectively, GDP per capita, and energy use per capita, the former seems to be much more important than the latter, for this precise collective intelligence. The energy use per capita seems to be just as instrumental, as the supply of money. The hypothesis that energy efficiency can be considered as an equilibrium rather than efficiency strictly spoken, seems to have some grounds.

The version of collective intelligence striving to optimize the coefficient of fixed assets per 1 patent application seems to be the most plausible representation of what the national economies under scrutiny actually do. It is interesting to have a closer look at how this collective intelligence is supposed to behave regarding individual variables in the game. Table 2, in the Appendix, compares the mean values of variables in the original set X, with the de-standardized means generated in the most likely scenario of optimizing the coefficient of fixed assets per 1 patent application, under linear standardization. This scenario assumes that energy efficiency would grow by 1,57%, accompanied by similar in scale growth in: a) the pace of technological change, measured with the share of aggregate depreciation in the GDP, and b) the percentage of urban population in the total population. Energy intensity, i.e. energy use per capita, is supposed to grow, although slightly, by 2,3%. Interestingly, such a (supposedly) likely scenario can sustain significantly larger (+11,09%), mean national population.

Conclusions

Empirical research presented above gives strong grounds to the working hypothesis to the article, namely that energy efficiency is rather an equilibrium than efficiency in the strict sense of the term. Further, speculative hypotheses arise, based on these results. The visibly strong orientation of the collective intelligence embodied in empirical data on optimizing the coefficient of fixed assets per 1 patent application suggests the existence of sexual selection function in the evolutionary spirit. Sexual reproduction means interaction between two types of organisms: female organisms, able to mix their own DNA with that coming from other specimens, whilst male organisms are able to parcel their own DNA and communicate it, without killing the recipient. Optimization of proportions between fixed capital and patent applications is very much akin such interaction. Fixed investment is partly, institutionally distinct from R&D, which generates patent applications. Capital providers are the female organisms, able to mix the new inventions with their current technological flesh, whilst researchers and developers of new technologies are the male organisms.

The presence of a sexual reproduction function suggests, further, the presence of sexual preference function. As we talk about human societies, the human function of sexual preference comes as the closest analogue, and thus female organisms select the male ones, rather than the other way around. The coefficient of fixed assets per 1 patent application reflects the relative comfort (or relative tightness) of social positions held by male organisms, i.e. the inventors. National economies by the empirical sample used for the here-presented research display a tendency to keep this coefficient fairly pegged and constant, rather than changing it instrumentally, for example in the view of greater an energy efficiency.

References

1) Akalpler, E., & Shingil, M. E. (2017). Statistical reasoning the link between energy demand, CO2 emissions and growth: Evidence from China. Procedia Computer Science, 120, 182-188.
2) Andreoni, V. (2017). Energy Metabolism of 28 World Countries: A Multi-scale Integrated Analysis. Ecological Economics, 142, 56-69
3) Ang, B.W., (2004), Decomposition analysis for policymaking in energy: Which is the preferred method?, Energy Policy 2004, vol. 32, pp. 1131–9. http://dx.doi.org/10.1016/S0301-)
4) Broto, V. C., Baptista, I., Kirshner, J., Smith, S., & Alves, S. N. (2018). Energy justice and sustainability transitions in Mozambique. Applied Energy, 228, 645-655.
5) Ceruzzi, P.E., 2005, Moore's Law and Technological Determinism : Reflections on the History of Technology, Technology and Culture, vol. 46, July 2005, pp. 584 - 593
6) Coelho, R. L. (2009). On the concept of energy: History and philosophy for science teaching. Procedia-Social and Behavioral Sciences, 1(1), 2648-2652.
7) David, P. A. (1990). The dynamo and the computer: an historical perspective on the modern productivity paradox. The American Economic Review, 80(2), 355-361.

8) Stradner, J., Thenius, R., Zahadat, P., Hamann, H., Crailsheim, K., & Schmickl, T. (2013). Algorithmic requirements for swarm intelligence in differently coupled collective systems. Chaos, Solitons & Fractals, 50, 100-114.
9) De Vincenzo, I., Massari, G. F., Giannoccaro, I., Carbone, G., & Grigolini, P. (2018). Mimicking the collective intelligence of human groups as an optimization tool for complex problems. Chaos, Solitons & Fractals, 110, 259-266
10) Duan, C., & Chen, B. (2018). Analysis of global energy consumption inequality by using Lorenz curve. Energy Procedia, 152, 750-755.
11) Edgerton, D. (2011). Shock of the old: Technology and global history since 1900. Profile books
12) Faisal, F., Tursoy, T., & Ercantan, O. (2017). The relationship between energy consumption and economic growth: Evidence from non-Granger causality test. Procedia Computer Science, 120, 671-675
13) Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt
14) Frontali, C. (2014). History of physical terms:'Energy'. Physics Education, 49(5), 564.
15) Fuller S, McCauley D. Framing energy justice: perspectives from activism and advocacy. Energy Res Social Sci 2016;11:1–8
16) Geels, F., Kern, F., Fuchs, G., Hinderer, N., Kungl, G., Mylan, J., Neukirch, M., Wassermann, S., 2016. The enactment of socio-technical transition pathways: a reformulated typology and a comparative multi-level analysis of the German and UK low-carbon electricity transitions (1990–2014). Res. Policy 45, 896–913
17) Hall, C.A.S., (1972) Migration and metabolism in a temperate stream ecosystem, Ecology, vol. 53 (1972), pp. 585 - 604.
18) Hardt, L., Owen, A., Brockway, P., Heun, M. K., Barrett, J., Taylor, P. G., & Foxon, T. J. (2018). Untangling the drivers of energy reduction in the UK productive sectors: Efficiency or offshoring?. Applied Energy, 223, 124-133.
19) Heiskanen, E., Apajalahti, E. L., Matschoss, K., & Lovio, R. (2018). Incumbent energy companies navigating the energy transitions: Strategic action or bricolage?. Environmental Innovation and Societal Transitions.
20) Heun, M. K., Owen, A., & Brockway, P. E. (2018). A physical supply-use table framework for energy analysis on the energy conversion chain. Applied Energy, 226, 1134-1162
21) Hoekstra R, van den Bergh JCJM. (2003), Comparing structural and index decomposition analysis, Energy Economics 2003, vol. 25, pp. 39–64, http://dx.doi.org/10.1016/S0140-9883(02) 00059-2
22) https://data.worldbank.org last accessed November 25th, 2018
23) https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS last accessed November 25th, 2018
24) https://data.worldbank.org/indicator/FM.LBL.BMNY.GD.ZS last accessed November 25th, 2018
25) https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG
26) https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS last accessed November 25th, 2018
27) Kline, R., Pinch, T., 1996, Users as Agents of Technological Change : The Social Construction of the Automobile in the Rural United States, Technology and Culture, vol. 37, no. 4 (Oct. 1996), pp. 763 - 795
28) Leonard, W.R., and Robertson, M.L. (1997). Comparative primate energetics and hominoid evolution. Am. J. Phys. Anthropol. 102, 265–281.

29) Liu, F., Yu, M., & Gong, P. (2017). Aging, Urbanization, and Energy Intensity based on Cross-national Panel Data. Procedia computer science, 122, 214-220
30) MacKenzie, D., 1984, Marx and the Machine, Technology and Culture, Vol. 25, No. 3. (Jul., 1984), pp. 473-502.
31) Mahoney, M.S., 1988, The History of Computing in the History of Technology, Princeton, NJ, Annals of the History of Computing 10(1988), pp. 113-125
32) Matschoss, K., & Heiskanen, E. (2018). Innovation intermediary challenging the energy incumbent: enactment of local socio-technical transition pathways by destabilisation of regime rules. Technology Analysis & Strategic Management, 30(12), 1455-1469
33) McKagan, S. B., Scherr, R. E., Close, E. W., & Close, H. G. (2012, February). Criteria for creating and categorizing forms of energy. In AIP Conference Proceedings (Vol. 1413, No. 1, pp. 279-282). AIP.
34) Moreau, V., & Vuille, F. (2018). Decoupling energy use and economic growth: Counter evidence from structural effects and embodied energy in trade. Applied Energy, 215, 54-62.
35) Mumford, L., 1964, Authoritarian and Democratic Technics, Technology and Culture, Vol. 5, No. 1 (Winter, 1964), pp. 1-8
36) Odum, H.T. (1971) Environment, Power, and Society, Wiley, New York, NY, 1971, Published by: The Johns Hopkins University Press on behalf of the Society for the History of Technology
37) Robson, S.L., and Wood, B. (2008). Hominin life history: reconstruction and evolution. J. Anat. 212, 394–425
38) Russon, A. E. (2010). Life history: the energy-efficient orangutan. Current Biology, 20(22), pp. 981- 983.
39) Solé, J., García-Olivares, A., Turiel, A., & Ballabrera-Poy, J. (2018). Renewable transitions and the net energy from oil liquids: A scenarios study. Renewable Energy, 116, 258-271.
40) Stradner, J., Thenius, R., Zahadat, P., Hamann, H., Crailsheim, K., & Schmickl, T. (2013). Algorithmic requirements for swarm intelligence in differently coupled collective systems. Chaos, Solitons & Fractals, 50, 100-114.
41) Su B, Ang BW., (2012), Structural decomposition analysis applied to energy and emissions: Some methodological developments, Energy Economics 2012, vol. 34, pp. 177–88. http://dx.doi. org/10.1016/j.eneco.2011.10.009.
42) Taalbi, J. (2017). What drives innovation? Evidence from economic history. Research Policy, 46(8), 1437-1453.
43) Velasco-Fernández, R., Giampietro, M., & Bukkens, S. G. (2018). Analyzing the energy performance of manufacturing across levels using the end-use matrix. Energy, 161, 559-572
44) Vincenti, W.G., 1994, The Retractable Airplane Landing Gear and the Northrop "Anomaly": Variation-Selection and the Shaping of Technology, Technology and Culture, Vol. 35, No. 1 (Jan., 1994), pp. 1-33
45) Wasniewski, K., (2017), Financial Equilibrium in the Presence of Technological Change, Journal of Economics Library, Volume 4 (2), June 20, s. 160 – 171, KSP Journals, Turkey, 2017
46) Wasniewski, K., (2017), Technological change as intelligent, energy-maximizing adaptation, Journal of Economic and Social Thought, Volume 4 September 3, 263-276, Turkey, 2017
47) Weng, Y., & Zhang, X. (2017). The role of energy efficiency improvement and energy substitution in achieving China's carbon intensity target. Energy Procedia, 142, 2786-2790.

48) Yu, S., Wei, Y. M., Fan, J., Zhang, X., & Wang, K. (2012). Exploring the regional characteristics of inter-provincial CO2 emissions in China: An improved fuzzy clustering analysis based on particle swarm optimization. Applied energy, 92, 552-562
49) Ziaei, S. M. (2018). US interest rate spread and energy consumption by sector (Evidence of pre and post implementation of the Fed's LSAPs policy). Energy Reports, 4, 288-302.

Appendix – detailed numerical results

List of links to accessory Excel files with mutations of the neural network, based on linear standardization over local maxima:

1) Output variable: GDP per kg of oil equivalent in energy consumed (the outcome variable) >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-energy-efficiency_educational.xlsx

2) Output variable: fixed assets per one patent application >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-fixed-assets-per-patapp.xlsx

3) Output variable: aggregate depreciation of fixed assets as % of the GDP >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-depreciation-in-GDP.xlsx

4) Output variable: number of resident patent applications per 1 million inhabitants >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-patent-applications.xlsx

5) Output variable: supply of broad money as % of the GDP >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-supply-of-money.xlsx

6) Output variable: energy use per capita >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-energy-per-capita.xlsx

7) Output variable: depth of food deficit per capita >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-food-deficit.xlsx

8) Output variable: % of renewables in the total consumption of energy >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-percentage-renewables.xlsx

9) Output variable: % of urban population in total population >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-percentage-urban-population.xlsx

10) Output variable: GDP >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-GDP.xlsx

11) Output variable: population >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-population.xlsx

12) Output variable: GDP per capita >> https://discoversocialsciences.com/wp-content/uploads/2019/09/Perceptron-with-big-database_pegged-GDP-per-capita.xlsx

Table 1 – Euclidean distances, computed with equation (8), between the original set of data X, and alternative sets Si, produced by the neural network under various assumptions of standardization, and optimization.

	Type of standardization in source data	
Output variable – orientation of the neural network	**Linear standardization over local maxima**	**Probabilistic standardization under cumulative Poisson distribution**
GDP per unit of energy use (constant 2011 PPP $ per kg of oil equivalent)	4,8104	43,4441
Fixed assets per 1 resident patent application	0,2375	15,2032
Share of aggregate depreciation in the GDP – speed of technological obsolescence	27,6499	57,2676
Resident patent applications per 1 mln people	2,1473	25,7709
Supply of broad money % of GDP – observed financial liquidity	17,6756	32,9519
Energy use (kg of oil equivalent per capita)	18,0154	33,2694
Depth of the food deficit (kilocalories per person per day)	4,9295	25,2644
Renewable energy consumption (% of total final energy consumption)	14,5858	31,6775
Urban population as % of total population	40,1487	39,2603
GDP (demand side)	3,2320	22,3782

GDP per capita	13,0649	34,2523
Population	3,5567	18,9141

Table 2 – The detailed structure of mean values generated by the neural network, with data standardized linearly over local maxima, and the coefficient of fixed assets per patent application as output variable

Input variable	Original means in the set X	Set generated when optimizing fixed assets per patent application, under linear standardization over local maxima	Percentage change
GDP per unit of energy use (constant 2011 PPP $ per kg of oil equivalent)	8,7243	8,8612	1,57%
Fixed assets per 1 resident patent application	**3 534,7977**	**3 534,7977**	0,00%
Share of aggregate depreciation in the GDP – speed of technological obsolescence	0,1415	0,1436	1,51%
Resident patent applications per 1 mln people	158,9010	182,8861	15,09%
Supply of broad money % of GDP – observed financial liquidity	74,6037	76,3418	2,33%
Energy use (kg of oil equivalent per capita)	3 007,2783	3 076,2986	2,30%
Depth of the food deficit (kilocalories per person per day)	26,4015	28,4511	7,76%
Renewable energy consumption (% of total final energy consumption)	16,0546	16,5039	2,80%
Urban population as % of total population	69,6993	70,4313	1,05%
GDP (demand side)	1 120 874,2300	1 243 155,1461	10,91%
GDP per capita	22 285,6265	22 982,3272	3,13%
Population	89 965 651,0513	99 939 461,5252	11,09%