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The paper analyses problems associated with technologies classification for the purposes of futures studies, in order to ensure definitive inclusion of technologies in specific classes/types when conventional approaches to classification are applied. The evolution of classification approaches in the scope of science philosophy is shortly reviewed, together with the latest research on expert-based and computerised (algorithmic) classification and methodological dilemmas related to hierarchical aggregation of technological and production processes are analysed. Common problems with classifying technologies and industries frequently encountered in the age of converging technologies are examined, using the agricultural sector and related industries as an example. A case study of computerised classification of agricultural technologies based on clustering algorithms is presented, with a brief analysis of the potential and limitations of the methodology. For doing so a two-stage approach to classifying technologies is suggested, based on distinguishing between platform (multipurpose) and industry-specific technologies. An adaptive approach to analysing technological structures is proposed, based on many-to-many relationships and fuzzy logic principles.

Keywords: classification, typology, futures studies, science and technology development, technological structure, industry structure, text mining, tagging, network structures, fuzzy logic

JEL: O14, O32, O33, Q16

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Introduction and Literature Review

Methodological problems related to technology classification and typology are very much relevant for virtually all fields of modern science, including futures studies. The importance of such challenges to futures studies, including technology Foresight, is due to the fact that in the long-term forecasting, research limitations imposed by perceiving structures as constant, and classification criteria as unwaveringly relevant, become crucial.

Cognitive problems attributed to relationship between atomistic phenomena, structures, and typologies remain at the centre of the epistemological discourse from antiquity (Brancacci, Morel, 2007; Wegner, 1986; Hull, 1965) to present day. Development of typology-, classification-, and taxonomy-related ideas is inherently linked to socio-economic and technological development of the society. During the Middle Ages a significant contribution to formulating relevant concepts and terminology was made by European scholastic philosophers, subsequently followed by outstanding naturalists such as Carl Linnaeus (Winsor, 2003) and Charles Darwin (Mayr, 1991), positivist philosophers, such as Auguste Comte and his classification of science (Comte, 1855), and then by members of the German sociology's formal school (Simmel, 1950). In the second half of the 20th century the evolution of scientific and philosophical understanding of similarity and differences between phenomena, and their hierarchy, was brought forward by modern philosophers such as Karl Popper (Wiley, 1975), Ferdinand de Saussure, Claude Lévi-Strauss (structuralism) (Glucksmann, 2014), and post-structuralism philosophers (Deleuze, Guattari, 1979), etc.

Basic formal logic concepts for objects' classifications have become sufficiently developed and definitive up to date. At the same time classifications applied in science and management still lack integrated theory and principles. They are designed intuitively often enough and based on subjective or expert consensus approaches where semantic delineation between "typology" and "classification" remains rather vague and ambiguous (Gokhberg, 2003). Typology- and classification-related issues in present-day scientific discourse are covered on a generalised level, with the focus of relevant publication activity shifting from philosophy and linguistics towards informatics and computer linguistics (Longobardia, 2009; Cheplygina, 2015; Witteveen, 2015; Sidorova, 2015; Hernández-González et al., 2015), as well as towards specific disciplines, problems, or practical activities (Allen et al., 2013; Bradbury-Jones et al., 2014; Darmania et al., 2014; Malek et al., 2014; Young et al., 2014; Dufva, 2015; Heurix et al., 2015; Venugopalana, 2015; Chen et al., 2015; Ho, Lee, 2015; Brown et al., 2015; Rozhkov, 2001; Beliayeva, 2011; Sirotkin, 2011; Shashnov, 2011, etc.). The best known classification practices for the R&D sphere, and methodological basis for international classifications designed by the UN and the OECD are presented in specialised manuals such as the Frascati Manual (OECD, 2005), the Oslo Manual (OECD, 2002), and the UNESCO recommendations on unification of national S&T fields classifications (UNESCO, 1984). They indicate classification-related problems, such as the need to develop special groupings for particular high-priority areas, comprising multiple segments of various standard institutional and functional classifications. The fact that international harmonisation of classifications inevitably requires classification groupings to be generalised, to a certain (frequently quite high) degree, is also noted.

In the interpretation of the terms "typology" and "classification" we largely adhere to the keynote paper by Alberto Marradi (1990). The author understands classification as a taxonomic (in line with the genus-species principle), or metrological (in line with the whole-part principle) division, or a series of sequential divisions based on a uniform defining criterion or a group of closely related criteria, resulting in a definitive inclusion of objects in specific categories (classes). Classifications may be hierarchic (complex) or flat (simple), natural (based on substantial, meaningful properties) or artificial (based on formal characteristics and created for specific functional purposes, for example a classification of dictionary entries broken down by alphabet letters). “Typology” is understood as a complex multidimensional classification based on a set of interconnected or orthogonal to each other, characteristics reflecting a research (study) concept and resulting, like ordinary classifications, in definitive inclusion of objects in specific categories (types). An example of a simple typology where overlapping criteria create definitive categories is a matrix where each cell contains all possible combinations of two criteria. A more complex variant would be a situation where not all criteria combinations define the types.

The main methodological difficulty in solving classification-related problems is finding the basis for classification. In practical research and especially in practical activities, such as public administration or strategic planning, the basis for classification is frequently chosen intuitively and subsequently adjusted empirically. Criteria for typology, as a more complex tool, are often selected using advanced quantitative analytical techniques. Statistical tools such as frequency analysis, intercorrelation matrices, factor analysis, and cluster analysis are usually applied. Along with this, due to the development of Big Data infrastructure, full-text analysis tools are increasingly applied to accomplish typology-related objectives. The very basic of them build topological concept clusters based on co-occurrence and co-concentration. Ones that are more complex include semantic groupings based on thesauri, parts-of-speech, and parts-of-sentence attribution.

Ongoing science and technology progress, advances of interdisciplinary studies, and convergence of technologies necessitate frequent reviews of classifications, and often require building two working classifications at the same time: one for activities relatively unaffected by dynamic processes, and the other for highly dynamic ones (Gokhberg, 2003). Definitive classifications based on a single criterion, or definitive typologies based on several characteristics are about to be replaced by fuzzy or overlapping classifications, or by tagging systems.

Analysis of methodological issues associated with building classifications for futures studies purposes’ is incomplete without considering the closely related aggregation problems. Aggregation of production is a less complex task than aggregation of technologies, because each production segment has specific input (raw materials) and output (semi-finished products, products) points. This allows to group production segments for management purposes into sub-industries, industries, and sectors of the economy, using raw materials- and products-based criteria. In the case of technologies, however, the problem becomes more difficult for two reasons. Firstly, technologies, as sets of codified knowledge, are universal unlike the production segments represented by physical objects (production facilities). Therefore, unlike in the case of production, a definitive “technology – raw materials” or “technology – product” connection cannot always be established, by far. Secondly, unlike production, technologies are fuzzy aggregates. Technological processes, embodied in actual physical equipment and hardware, can define each specific production facility. However, generally it is not possible to disaggregate a technology definitively into specific technological processes (“atomistic units” with specific sole input and output points).

The second of the above aspects determines the relevance of producing future-oriented statistics. The importance of this research area is because short-term forecasting mostly operates in quantitative variables in the scope of a given industry, technology, and market structure, whereas futures studies deal in long-term horizons where the constant structure premise ceases to hold true.

The aim of the paper is to propose a consistent approach to analytical decomposition of industries and relevant technologies, which could be efficiently operationalised as industry-specific thematic classifications, as well as provide sufficient flexibility for application in futures studies (a priori expecting significant changes of existing structures).

The importance of issues related to analytical decomposition not just of the whole economy (into sectors and industries), but of specific industries are also noted. The latter represents areas with overlapping segments, at least public and corporate ones (Andersen et al., 2014), complex overlapping of economic activities and economic agent types (business models), producers, consumers, and producers-consumers (active consumers). However, these and certain other analytical decomposition aspects were left outside the scope of this study.

Platform technologies and technological inheritance

Given the classification-related problems arising in the course of technology mapping described in the introduction and literature review section, primarily caused by convergence of technologies, we propose to adopt the “platform technologies” term to describe technologies applied, or potentially applied in multiple sectors of the economy or having multiple applications in one sector. It is also important to consider organisational innovations along with technological ones, since adopting new business models frequently requires adjusting production systems in order match new technological reality (see figure 1).

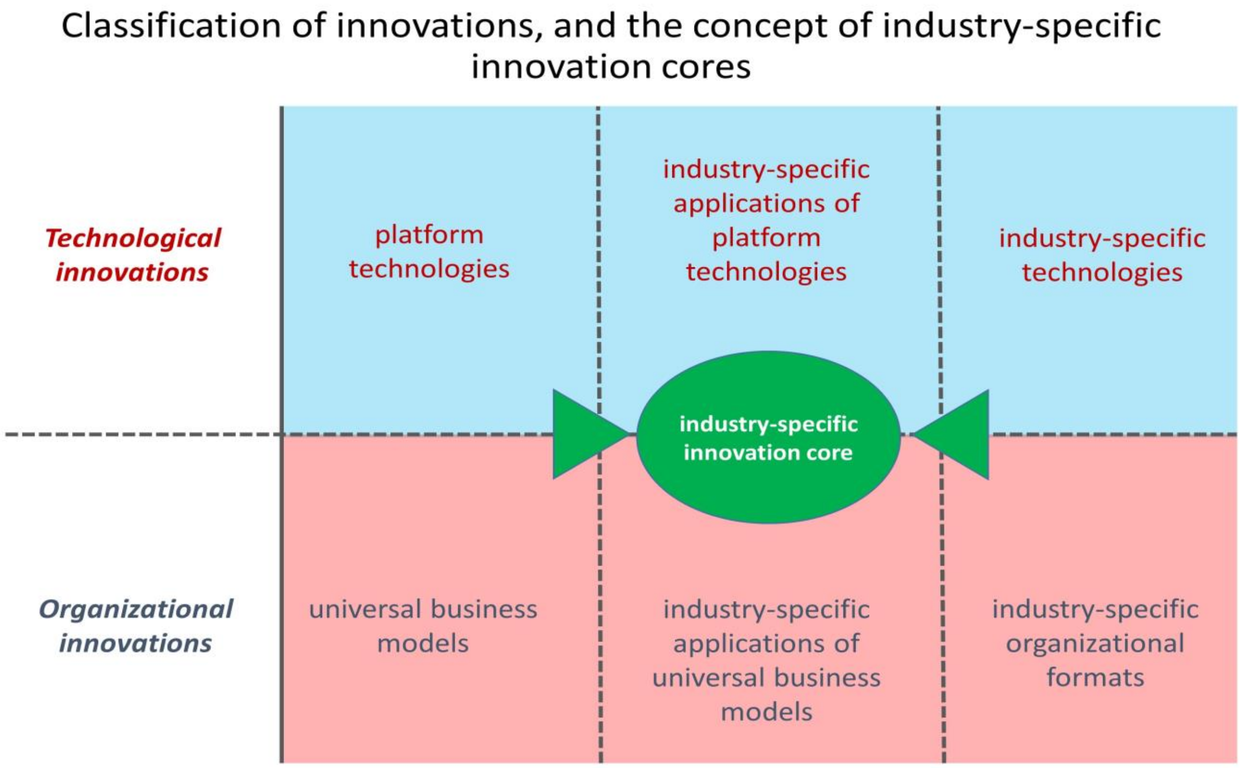

Figure 1. Approach to technology Foresight based on the platform technologies concept

It shows that the overlapping problem encountered in course of classifying technologies can be solved by adopting a two-stage classification procedure: at the first stage technologies are broken down by the scope of their application, and at the second one they are classified by industry, indicating industry-specific applications of those with a broader scope.

Here the difference between critical and platform technologies must be noted. Though according to certain formal definitions (e.g. Popper et al., 1998), critical technologies are the ones ubiquitously applied in various industries, the context of relevant publications reveals that the authors mean only those of the ubiquitously applied technologies which are radically important to the integrity of the economy (usually the national). Therefore, in the author's opinion critical technologies should be seen as a subset of platform technologies.

An important concept for analysing technologies in terms of their universality (application scope) is inheritance. Inheritance relations link platform technologies and their industry-specific applications. It means that industry-specific applications have basic properties inherent to the parent technologies, plus certain independent properties not present at the platform level. At the same time, industry-specific technologies can be linked by inheritance relations only with other industry-specific technologies, in the scope of relevant industries' aggregation hierarchies. In the framework of the proposed approach, industry-specific applications of platform technologies can take the form of individual technologies or technological complexes, among other things comprising certain industry-specific technologies. In that sense, industry-specific applications can inherit simultaneously from broad-scope platform technologies, and from industry-specific technologies.

It should be noted that breaking technologies down into platform ones, industry-specific applications of platform technologies, and narrow-scope industry-specific technologies can be validated quantitatively; this would require computerised full-text analysis tools (text mining), first of all statistical and semantic clustering. Building document samples for analysis in a correct way becomes crucially important. A set of documents for text mining techniques application should be sufficient in terms of volume (at least hundreds of forecasting analytical reports comprising at least millions of words), as well as include documents covering specific industries, describing R&D stages, experimental prototype application, and commercial application of technologies – as opposed to the basic research stage. It is essential that the sample is unbiased (does not contain documents primarily of one type or by one author etc.). Examples of platform and industry-specific technologies are provided below for the agricultural and forest industry sectors. The first case illustrates inheritance relations between platform technologies and their industry-specific applications. It clearly highlights the methodological problem connected with the platform technologies' hierarchy (see table 2).

Table 1. Platform technologies' hierarchy: the case of agricultural (AS) and forest industry (FIS) sectors

<table>
<tr><th>First-order platform technologies</th><th>Second-order platform technologies</th><th>Application industries</th><th>Industry-specific applications (inheriting technologies) (examples)</th></tr>
<tr><td rowspan="4">Biotechnology</td><td rowspan="2">Genetic modification</td><td>AS</td><td>Genetically modified crops specifically resistant to particular kinds of herbicides</td></tr>
<tr><td>FIS</td><td>Plantations of genetically modified extremely fast-growing trees</td></tr>
<tr><td rowspan="2">Synthetic biology</td><td>AS</td><td>Microorganisms for butylene- and isobutyl-based fermentation of agricultural waste</td></tr>
<tr><td rowspan="2">FIS</td><td rowspan="2">Microbiology-based technique for producing nanocellulose from timber</td></tr>
<tr><td rowspan="2">Nanotechnology</td><td rowspan="2">Production of organic nanostructured materials</td></tr>
<tr><td>AS</td><td>Chemical-based technique for producing nanocellulose (microfibrillary cellulose) from beet pulp</td></tr>
<tr><td rowspan="2">Geotechnology</td><td rowspan="2">Production of geotextile</td><td>AS</td><td>Application of geotextile for soil preservation</td></tr>
<tr><td>FIS</td><td>Application of geotextile for forest road building</td></tr>
<tr><td rowspan="2">Space technology</td><td rowspan="2">Geopositioning</td><td>AS</td><td>Driverless agricultural machinery</td></tr>
<tr><td>FIS</td><td>Tracking timber origins' legality</td></tr>
<tr><td>...</td><td>...</td><td>...</td><td>...</td></tr>
</table>

The above example shows that as technology convergence deepens, platform technologies that even recently were seen as being at the top of aggregation hierarchy cease being such. The case of emerging microbiology-based nanocellulose production technology illustrates convergence of nano- and biotechnologies into a new nanobiotechnology platform[5]. Therefore in the above example we have either to decide to adhere to the original decomposition (which would mean moving on from using a classification to a tree-like overlapping structure), or to add a new hierarchic level to the classification ("zero-order platform technologies") and review the level structure (make it more detailed, i.e. introduce first- and second-order platform technologies).

It should be noted that the problem of having to reclassify technologies as technological

[5] It should be noted that this case can be validated with text mining results (see table 3) which confirm that the "nanobiotechnology" term became sufficiently popular in recent years.

development moves on can be solved by adopting rhizomatic (hypernet) structures; matrixes allowing for multiple overlapping, and tagged lists can serve as simplified approximations thereof.

The second AS and FIS case illustrates industry-specific technologies which can produce identical products (see table 2).

Table 2. Independent technologies producing similar products

<table>
<tr><th>Industry</th><th>First-order subindustry</th><th>Second-order subindustry</th><th>Technology</th><th>Primary product</th><th>Secondary product</th></tr>
<tr><td>AS</td><td>Food industry</td><td>Sugar industry</td><td>Beet syrup evaporation</td><td rowspan="3">A variety of sugars</td><td rowspan="3">(a) ...

(b) Alcohol products (made by microbiologic fermentation)

(n) ...</td></tr>
<tr><td>AS</td><td>Animal breeding and beekeeping</td><td>Beekeeping</td><td>Extraction of honey from beehives</td></tr>
<tr><td>FIS</td><td>Wood chemical industry</td><td>Hydrolysis industry</td><td>Wood hydrolysis</td></tr>
<tr><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td></tr>
</table>

The above case shows that if to group technologies by product (a quite common methodological technique in futures studies), by sugar or alcohol products in this example, industry-specific groupings matching such technologies ("sugar industry", "spirits industry") can be essentially wrong while appearing to be formally right. This is because specific technical (and therefore marketing) production factors are not taken into account, first of all raw materials, and resulting geography- and organisation-related features of industries.

However, such grouping can have a predictive potential. Specifically, the hydrolysis industry is never included in the sugar industry because products made by hydrolysis of cellulose and lignin with application of sulphuric acid and other chemicals require complex and expensive treatment before they can be applied in the food industry. In addition, bee honey remains so expensive that it is never used to make technical spirits. Though, technological innovations (let us notionally call them "pure hydrolysis" and "robotic bees") in principle could potentially change the situation, so production of honey would gravitate towards the biofuel industry, while wood hydrolysis – towards the food industry. The example shows that in futures studies the situation of complete reversion should never be completely disregard. The only structure suitable for such analysis is a network one. Conventional classification structures cannot be applied for this kind of analysis.

Future-oriented composite grouping

Classification of economic activity types in the Russian Federation provides a convenient example that highlights different needs for a composite statistical grouping applied for current public administration purposes and for supporting the national strategic planning (and therefore in futures studies which provide information support for such planning).

It should be noted that OKVED-2 (the Russian National Classifier of Economic Activities, revised version) was improved compared to the OKVED-1 in terms of the classification's precision (Surinov, 2013). As an example, in the OKVED-1 the class "Agriculture, hunting, and provision of related services" included subclasses "Gathering forest mushrooms and truffles" and

“Gathering wild fruit, berries, and nuts”. At the same time, the section “Forestry and provision of related services” included subclasses “Gathering wild-growing and non-timber forest products”. The new OKVED-2 is largely free of such drawbacks and provides an acceptable decomposition of economic sectors and industries for statistical and ongoing administration purposes.

Considering relationship between activity types included in the agricultural sector or related to it on the one hand, and responsibilities of the respective federal executive agency (the Russian Ministry of Agriculture) on the other, shows that at the highest level, each of the main Ministry of Agriculture’s responsibilities has a matching class of economic activity types. However, asymmetries appear at subclasses levels, which are supervised by different federal executive agencies. For instance, the class “Plant growing, animal farming, hunting, and provision of related services” includes six subclasses whose activities are supervised by the Ministry of Agriculture, and one subclass that happens to be a responsibility of the Russian Ministry of Natural Resources and Environment (“Hunting, catching, and shooting of wild animals, including provision of related services”).

Also, the consensual expert understanding of the agricultural sector’s composition does not match either the responsible ministry’s mandate, or the classification of economic activity types – because three such proto-classifications were designed taking into account only partially overlapping factors. Accordingly, as a result of these stochastic processes, the Russian Ministry of Agriculture’s responsibilities (and it is the agency responsible for shaping government policy, and legal administration of the agricultural sector) do not include production of fertilisers and agricultural machinery, which most experts believe to be segments of the agricultural sector.

A structure of a possible composite grouping for the agricultural sector and the relevant executive agency’s mandate, are presented in figure 2.

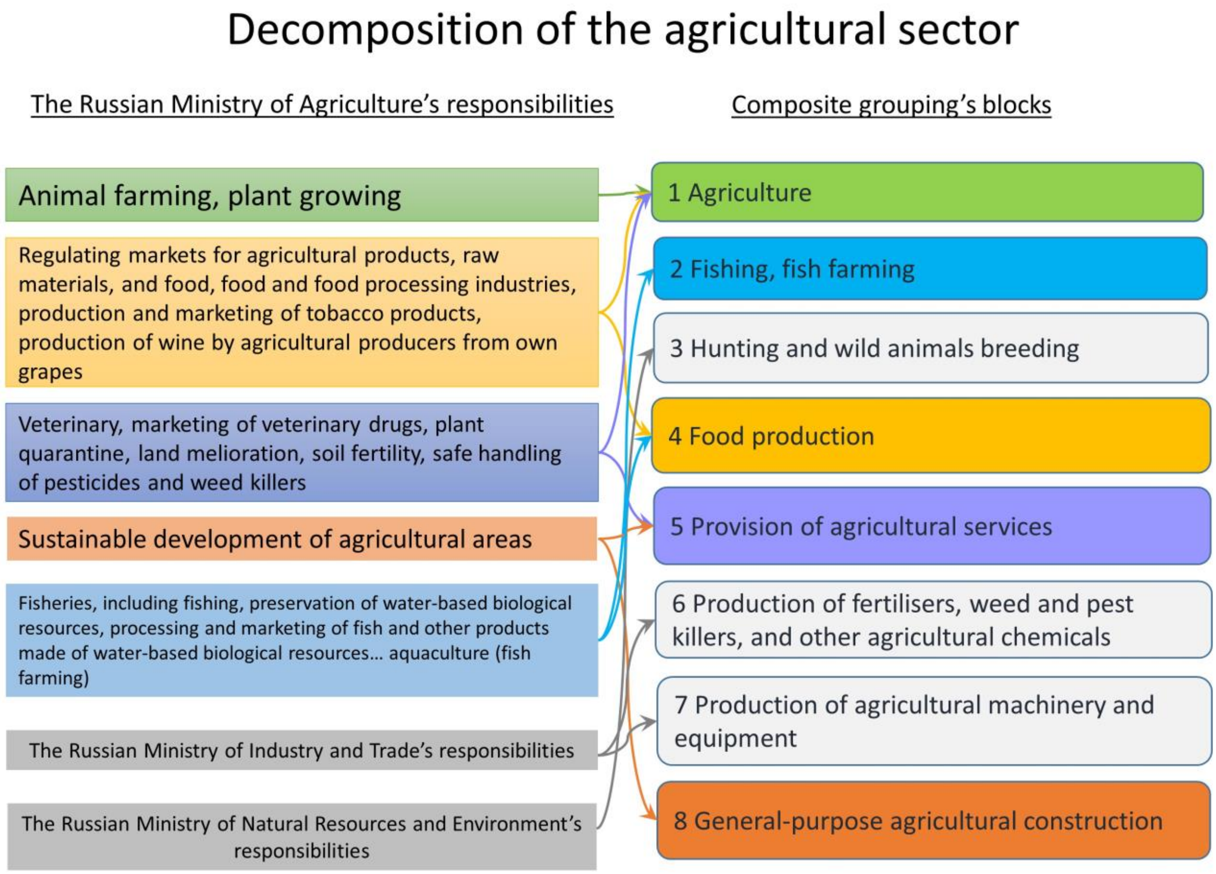

Figure 2. Decomposition of the agricultural sector: administrative and economic aspects

While providing a reasonable solution for practical problems with synchronising administrative and economic aspects of the agricultural sector's decomposition, the above scheme still does not match futures studies' needs. To meet relevant requirements such (sub)-classes as "Other production" and "Innovative production", on all hierarchy levels should be included in in the composite grouping. It should be noted that the OKVED-2 does have some subclasses with similar functionality. For example, the subclass "Production of fertilisers and nitrides" includes the second-order subclass "Production of fertilisers not included in other groupings". The class "Production of chemicals and chemical products" includes the subclass "Production of pesticides and other agricultural chemicals". "Other" categories allow avoiding the need to review the classification in line with the S&T development frequently (e.g. emergence of "smart fertilisers", capsule multilayer fertilisers, weed and pest killers based on new, for example, biomimetic principles), though it still does not provide predictive tools for futures studies.

An approach to studying structures the authors believe to be essential for futures studies is presented in figure 3.

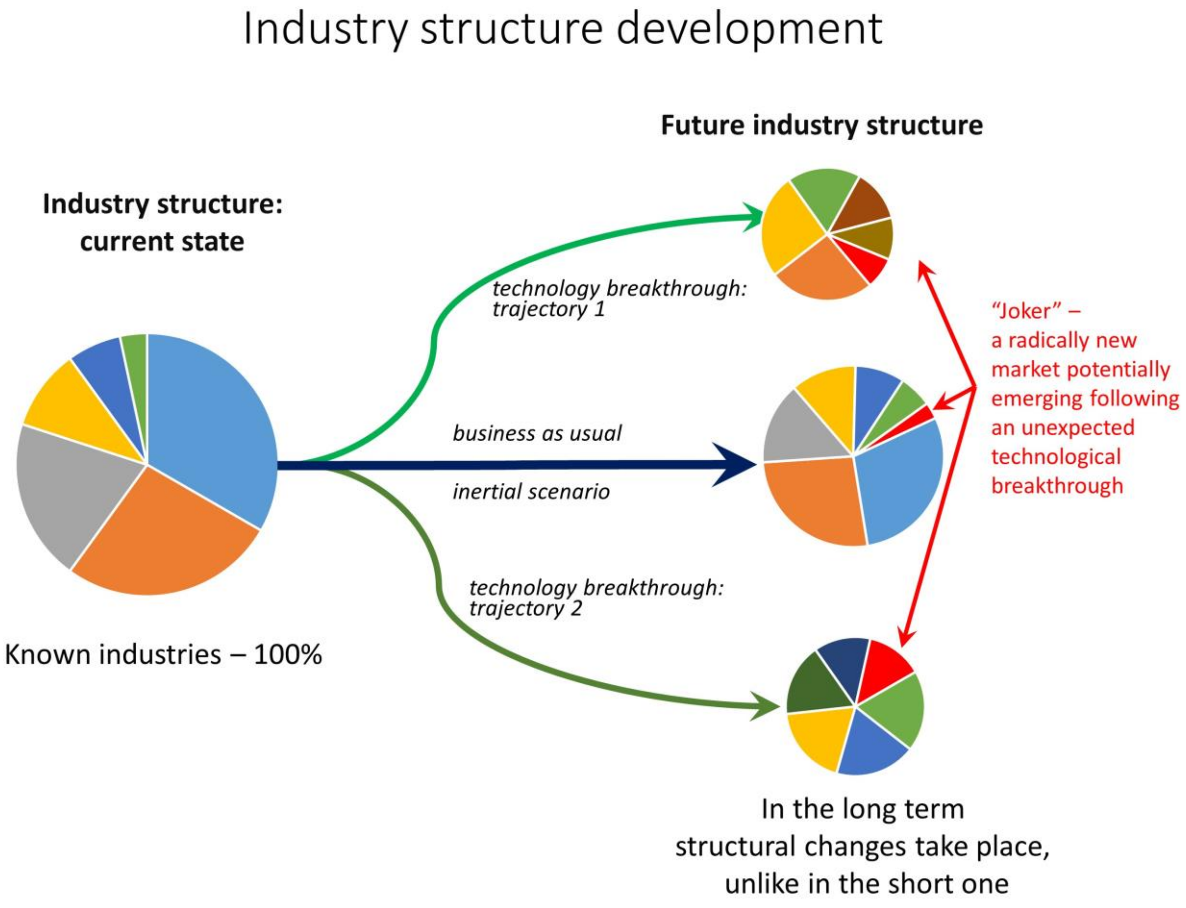

Figure 3. Futures studies' basic assumption of changing structure

The principle described above implies that for making long-term forecasts we should always expect the structure to change and that does not allow to using classifications reflecting the current state of affairs. At the same time, changes of the industry structure are preceded by changes of the technological one. Emergence of a new technology initially leads to a change of the technological structure (the codified knowledge structure) and then, in case there is a resonance between supply (the new technology) and demand (for products with new consumer properties), the changes in the technological structure transform into changes in the industry structure (the structure of material objects, i.e. production facilities).

Whereas for all kinds of short-term forecasting, and for basic socio-economic forecasting the assumption of changing structure is unnecessary, and it is not taken into account for model simplification purposes, in long-term industry-specific forecasting and technology Foresight studies this assumption, in the authors' opinion, is essential.

Automating classification-related tasks through application of text mining

Subjective classifications (built by individual researchers), and collective-subjective ones (based on expert consensus) in essence amount to explication of expert knowledge. In its turn, expert knowledge is acquired by long-term accumulation of information learned through verbal or written communication. Knowledge transferred via verbal speech sooner or later finds its written expression. Since the speed of human perception of information is limited, while the amount of text-based information is growing all the time, it becomes increasingly important to view expert knowledge as a narrow, biased sample of codified knowledge. Therefore building classifications by clustering performed via computerised analysis of large volumes of full-text sources (for example, text mining) is just an alternative to the expert-based technique for interpreting and aggregating codified knowledge. Under certain conditions, this method can be more efficient than explicating expert knowledge. Probably in future the role of this information processing technique would only grow, which is confirmed by the growing interest researchers display to the problem of limited expert knowledge and development of fuzzy logic-based research models (including fuzzy cognitive maps) in various scientific domains, futures studies in particular (Jetter, Kok, 2014).

As an example demonstrating the most simple, basic text mining potential, an incomplete (with a certain cut-off threshold for frequency of occurrence and proximity of search terms), technology-clustering table for the agricultural sector is presented below. It was produced with the help of computerised analysis of an array comprising 600 full-text documents (industry forecasts, market research reports and other industry-specific analytical papers mostly published by the OECD) on agricultural and related topics, using originally designed algorithms. In this simple example, a single stem (unchanging part of word) was used as the starting point for clustering: *techno*. The fact that clustering allows flexibly measure the degree of words' proximity partially solves the problem of not all technologies in the text (not by far) being denoted with word combinations (n-grams) which include the stem *techno*. In other words, when a technology is mentioned in a text, the stem *techno* is likely be found not far from the reference to this technology. The distance could be up to four words (in the given example, clustering was limited to uni-, bi-, tri-, and quadrigrams), or even several sentences, but if the volume of source data is large enough, proximity between the stem *techno* and n-grams denoting technologies in most cases will be established. Still, application of more complex clustering algorithms (with multiple starting points, and semantic tools) would yield more comprehensive results than the ones in our example (table 3)[6][7].

[6] For convenience purposes, the stem *techno* in the table was lemmatised to the form *technology*

[7] It should be noted that an additional benefit of such clustering is the fact that technology-related aspects specifically linked with particular technology groups are also identified (such as particular fiscal of organisational solutions, etc.). This enriches the semantic field for the analysis and allows to subsequently make higher-quality expert conclusions

Table 3. Clustering agricultural sector technologies using text mining techniques

Cluster	tf	Cluster members
TECHNO (occurrence rank: =71; occurrence coefficient **tf**: =7,497)		
biotechnology nanotechnology nanobiotechnology genetic technology	1,1260 0,2098 0,0022 0,0008	agricultural biotechnology, plant biotechnology, animal biotechnology, crop biotechnology, microbiology biotechnology, ICT biotechnology, industrial biotechnology, nanotechnology biotechnology, pesticides biotechnology, food biotechnology, marine biotechnology, breeding biotechnology, environmental biotechnology, livestock biotechnology, cotton biotechnology, ecological biotechnology, green biotechnology, Mendel biotechnology, survival biotechnology, bank agricultural biotechnology, agricultural biotechnology council, environmental threats biotechnology, perceived environmental threats biotechnology, material nanotechnology, biology nanotechnology, communication nanotechnology, ICT nanotechnology, mechatronics nanotechnology, nanotechnology geotechnology, biotechnology nanotechnology, proteomics nanotechnology, nanobiotechnology, genetically modified plants, genetically modified crops, genetically modified organisms, genetically modified foods, inheritance genetic stability, plant genetic systems, genetically engineered organisms, crop genetic improvement, genetically engineered crops, genetically modified cotton, forest genetics council, genetically engineered animals, genetically engineered varieties, unintended effects genetic modification, genetically modified rice, genetically modified corn, genetically modified microorganisms, Douglas fir silvae genetica, genetic resource base, genetically modified feedstuffs, inbreeding depression genetic load, EnviropigTM genetic technology meeting
agrotechnology agricultural technology agritechnology	0,0270 0,0150 0,0037	materials agrotechnology, agrotechnology sector, advanced agrotechnology, fund agricultural technology, information guidance technology, agriculture contextual information, networks information technology, contextual information network, green agricultural technology, farming technology, varieties farming technology, labour-saving farming technology, farming technology farm size, crop cultivation technology, wheat cultivation technology, maize wheat cultivation technology, paddy rice cultivation, market gardening flower cultivation, greenhouses vegetable cultivation, scientifically established cultivation technology, intensive rice cultivation, upland crop cultivation, low-intensive cultivation, oil seeds cultivation, cultivation rain-fed crops, cultivation rapeseed vegetable oil, cultivation staples small-holdings, cultivation using animal traction, wine cultivation steep slopes, cultivation far southern steppes, soil water conserving cultivation, water conserving cultivation practices, cultivation higher rainfall areas, cultivation marginal land producers, cultivation using motorized mechanization
ecotechnology green technology environmental technology conservation technology sustainable technology	0,0052 0,0022 0,0017 0,0011 0,0010	green technological foresight, green technology promotion, green revolution technology, OECD green growth, green growth studies, green growth fisheries, green growth indicators, green growth strategy, green growth aquaculture, green growth blue, green growth initiatives, cap greening measures, environmentally friendly technology, alternative environmentally acceptable technology, environmentally sound technology, environmentally sound infrastructure technology, environmental taxes, agrienvironmental public goods, externalities agrienvironmental policy, cost-effective agrienvironmental policy, environmental quality incentives, environmentally friendly farming, negative environmental impacts, environmental impact assessment, agrienvironmental footprint index, environmentally related taxes, monitoring environmental efficiency, negative environmental externalities, environmentally friendly agriculture, environmental effects dairy, evidence-based agrienvironmental policies, environmental cross compliance, environmental taxes tradeable, environmentally harmful subsidies, agrienvironmental public bads, climate change mitigation technology, agricultural mitigation technology, adaptation mitigation technology, mitigation technology bioenergy, CDR technology, carbon dioxide removal CDR, dioxide removal CDR technology, LEISA technology, EISA organic biotechnology, scaling LEISA approaches, adopt labour-intensive LEISA, difficulty scaling LEISA, farmers adopt LEISA, gm crops LEISA, inter-temporal impacts LEISA, labour-intensive LEISA approaches, large-scale adoption LEISA, LEISA technology liquidity, rapidly scaling LEISA, restrictive forms LEISA, strictly prohibited LEISA, sustainable agriculture LEISA, environmentally sustainable biotechnology, maximum sustainable yield MSY, sustainable agricultural productivity, sustainable productivity growth, sustainable forest management, sustainable farming fund SFF, sustainable land use, sustainable land management, sustainable crop protection, sustainable rural development, sustainable fisheries aquaculture, sustainable farming practices, smart sustainable inclusive growth, sustainable natural resource management, sustainable management water resources, discontinued sustainable development technology, genetically modified plants sustainable, low

		external input sustainable agriculture LEISA, sustainable exploitation fisheries resources, sustainable water quality management, act RMA sustainable farming, RMA sustainable farming fund
irrigation technology	0,0044	irrigation water, irrigation systems, drip irrigation, irrigation drainage systems, irrigation infrastructure, irrigation schemes, on-farm irrigation, irrigation facilities, North Otago irrigation, irrigation equipment, fertiliser irrigation, irrigation acceleration fund, community irrigation, pressurised irrigation, community irrigation fund, irrigation canals, irrigation channels, irrigation networks, irrigation techniques, large-scale irrigation, plantations irrigation, roads irrigation, supplemental irrigation, flood irrigation, irrigation freshwater, effluent irrigation, groundwater irrigation, precision irrigation, small-scale irrigation, surface irrigation, crop irrigation, directed irrigation, irrigation electricity, irrigation fertilization, irrigation well, outlays irrigation, rehabilitation irrigation, tillage irrigation, excessive irrigation, inappropriate irrigation, participatory irrigation, transport irrigation, wastewater irrigation, micro irrigation, micro-irrigation systems, saving irrigation technology, mini-irrigation drip technology, water-conserving irrigation technology, water-saving irrigation technology, industrial drip irrigation, Otago irrigation company, water saving irrigation, irrigation drainage infrastructure, national irrigation commission
energy technology fuel technology	0,0019 0,0008	renewable energy technology, new energy technology, energy saving technologies, alternative energy technology, decentralised energy technology, renewable energy technology, solar energy technology, energy technology waste, energy technology platform, fuel tax exemptions, fertiliser biofuel policies, advanced biofuels technology, fuel cell technology, biofuel support policies, renewable fuel standard, biofuel budgetary support, fuel tax concessions, first generation biofuels, fuel standard RFS, second generation biofuels, renewable fuels standard, advanced biofuel mandate, fuel excise tax exemption, flex fuel vehicles, abolishing biofuel mandates, hydrous ethanol fuel, biofuel blending mandates, biofuels produced lignocellulosic biomass, advanced cellulosic biofuel mandates, agriculture food fiber fuel, biofuel mandate subsidy equivalent, biofuel mandates EISA EPA, biofuel production limited feedstock, low carbon fuel standard, water implications biofuels production, market assessment biofuels cereals
processing technology	0,0013	food technology, food processing technology, grain circulating processing technology, ethanol processing technology, signal processing technology
sensor technology	0,0013	sensor robotics, biosensor technology, sensors actuators, sensor systems, sensor data, sensor types, sensors GPS satellites, remote sensors, satellite sensors, sensor-based systems, onboard yield sensors, wide field-of-view sensor, implanted sensors, infrared sensors, artificial intelligence sensors, low-cost sensors, multiple sensors, nanosensors nanofluidics, pervasive sensors, electrical resistance sensors, sensor networks, sensors greenhouse gases, sensors greenhouse equipment, tactile sensors, thermo sensors, Norias thermo sensors, sensors monitor temperature, sensor online assessment, machine vision sensors, sensor technology foresight, hidden features sensors, computer systems interrogate sensors, sensors Samsung Galaxy
saving technology	0,0011	moisture-saving technology, water saving technology, moisture water saving technology, farms USDA moisture-saving technology, labour-saving technology, labour time-saving technology, irrigation water-saving technology, irrigation water-saving technology desalination, water-saving technology desalinisation conservation, river extension water-saving technology, sprinkler systems water-saving technology, moisture-saving technology reduced tillage, promote cost-saving technological innovations

Tag structure for analysing technology landscape for futures studies purposes

As discussed earlier, classifications are poorly suited for working with overlapping sets, technologies in particular. Therefore, attempts to build a technological classification for any industry based on consensus of experts will be inevitably inefficient due to a large number of specific cases about each experts may have irreconcilable opinions, among other things for economic reasons (for example, when classification is built for subsequent priority setting for allocation of public R&D funding). A simple solution apparently provided by adding the "Other" category may work in some cases, but the "Other" class may result in becoming the biggest in the whole classification. Introducing the "Other" category for the purposes of classifying existing technologies and priority-setting should not be confused with introducing the same category for Foresight studies-related purposes, on the basis of the fundamental premise that structures are going to change.

It should also be noted that a classification which includes an "Other" category comprising all items, which cannot be definitively attributed to specific classes, would be a case of a confluent intersection matrix "classes X objects", in which each object can belong in more than one class. In turn, such a matrix which can only have values "yes" and "no" at intersections of rows and columns (the object does or does not belong in the class) is a specific case of a matrix where objects' attribution to particular classes is weighted using a certain range of values (for example, any number between 0 and 1). Such values may be assigned based on expert consensus, for instance, through a Delphi survey. However, moving on we inevitably start assigning such weights using computers (based on text mining algorithms), for subsequent adjustment by experts. This approach is a specific application of the fuzzy logic concept that belongs in the informatics area (in fuzzy logic, Boolean variables (true-false) can have not just the two values, 0 and 1, but any value within the 0-1 range).

The following tag structure for analysing technology landscape can serve as a representation of the above-described matrix, in a format convenient for human perception and freed from the previously mentioned drawbacks typical to conventional classifications and typologies. It is flexible to reflect any shifts in the technology landscape caused by S&T development, disruptive innovations, and convergence of technologies:

- industry-specific technology;
- hyperlink tree to parent technologies, with weights denoting tie strength;
- hyperlink tree to technology application industries, with weights denoting tie strength;
- hyperlink tree to new industries/sub-industries likely to be engendered by the technology;
- the technology's development stage - R&D, prototype, test application, market expansion, stagnating demand, declining demand (not to be confused with technology readiness level (TRL), which does not allow to measure technologies' market situation).

Conclusion

The paper analysed various issues of classifying technologies for futures studies purposes. Analysis of literature revealed that classification- and typology- (as a form of classification) related problems became particularly relevant in the era of convergence. There is also a clear shift of researchers' interest towards developing computerised data processing algorithms for classification and typology-building purposes, including algorithms for processing natural language and analysing large volumes of full-text sources (text mining). The trend of replacing classification toolset emerges. In all probability, rhizomatic (hypernet) structures based on fuzzy logic principles will step in as such a replacement.

Analysis of methodological tools for building classifications allowed identifying major problems with applying this method of learning in futures studies. These problems mainly amount to impossibility, in the scope of conventional classifications and typologies, of including an object in two or more different classes (types) at the same time. It was demonstrated that this issue is particularly relevant for mapping prospective technology landscape, while for the purposes of reflecting the existing industry structure and setting development priorities it is not as acute, and in certain cases is completely irrelevant.

Analysis of causal relationships between technological innovations and dynamics of production structure allowed to demonstrate that changes in the structure of technologies take place first, and subsequently may lead to changes in the production structure (for example, material objects such as production facilities where specific technological processes are applied), if demand and supply factors happen to create a synergy. This means that future technology structures should be seen as a major subject area of futures studies including futures studies, because they allow to foresee future structure of the economy and social, environmental, and other aspects of future society it determines, as an environmental, economic, and information system.

In line with L. Gokhberg's views on classification types (Gokhberg, 2003), the paper analysed expert- and machine-based classification techniques and presented a case of clustering agricultural sector technologies using originally developed algorithms. Results of technology clustering can be fuller and more precise if in addition to statistical text mining techniques, semantic methods are applied. Such algorithms can significantly reduce the need for experts' input to develop conventional classifications and fuzzy network systematisations of technologies, products, markets, and other objects and phenomena alike.

Using the agricultural and forest industry sectors as examples, problems associated with conventional technology classifications were highlighted. As a provisional solution, a two-stage approach to classifying technologies was proposed: at the first stage technologies are divided into platform and industry-specific ones, on the basis of the scope for their application, after which technologies are classified into industries and sub-industries, identifying industry-specific applications of platform technologies and industry-specific technologies which do not inherit their characteristics from technologies applied outside of the industry in question. It was also demonstrated that this approach is not without drawbacks and requires frequently reviewing data models (classification structures) as technology convergence deepens in the scope of the new emerging technology wave.

Accordingly, we argue that futures studies should gradually shift from using classifications to adapting matrix, network, and tag analytical structures that offer a much broader scope and flexibility.

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