Universal Intelligence, Creativity, and Trust in Emerging Global Expert Systems

Andrzej M.J. Skulimowski[1,2]

[1]AGH University of Science and Technology, Chair of Automatic Control and Biomedical Engineering, Decision Science Laboratory, 30-050 Krakow
[2]International Centre for Decision Sciences and Forecasting, Progress & Business Foundation, 30-041 Kraków, Poland
e-mail: ams@agh.edu.pl

Abstract. This paper presents a hypothesis together with evidence related to the use of global knowledge as a holistic expert system. By global expert system (GES) we mean all knowledge sources, bases, repositories, and processing units, regardless of whether they are human, artificial, animal, or hybrid, such that the relation "*able to transfer knowledge on immediate demand*" forms a connected graph over the elements of the system. A key requirement is that problem solving using GES is an anytime process with respect to the number of information sources taken into account. We conjecture that due to the high and ever-growing level of interconnection of knowledge units, a universal intelligence emerges, which under specific conditions can outperform the intelligence and creativity of any of its individual elements, including humans. It will be shown that this is possible only if an appropriate level of credibility can be assigned to each element of the system, which ensures that users trust the responses. We will design a hybrid supervised-reinforced learning scheme that makes it possible to achieve a satisfactory level of trust in GES query responses. Query processing will apply knowledge fusion methods such as combinations of recommendations and forecasts.

Keywords: Global expert systems, big data, universal intelligence, trust management, semi-supervised learning, foresight

1 Introduction

This paper presents several problems related to the emergence of global knowledge regarded and used as a holistic global expert system. By a global expert system (GES) we mean all knowledge sources, sensors, bases, repositories and processing units, regardless of whether they are human, artificial, animal, or hybrid, provided that they are mutually connected and endowed with an information management system with the usual expert system functionalities. Specifically, in a GES the relation "able to transfer knowledge on immediate demand" forms a connected graph over the elements of the global knowledge system.

The interest in GES results mainly from the emergence of global information exchange networks powered by search engines and autonomous network crawlers.

Three general development trends related to GES have been identified within the research project [18]:

- a growing level of integration of heterogeneous information sources
- a growing number of interconnected knowledge units
- an increase in the amount of information and sophistication of information processing within individual units.

These are supplemented by qualitative trends regarding the degree of refinement of the information stored and processed in each unit according to the well-known scheme: information→knowledge→wisdom. Other trends touch upon the structure of this information. For instance, the percentage of all data stored on the web and indexed by the Google search engine rose from 1% in January 2007 to 6% in January 2010 and exceeded 10% in January 2012. At the same time, the estimated amount of information on the web rose to 800 exabytes and the number of web sites exceeded 560 million (cf. e.g. [21] and further links there). When the tools offered by search engines become increasingly sophisticated, this system of interconnected web sites becomes a real GES endowed additionally with a variety of analytic methods.

The second source of inspiration for the underlying research comes from studies on collective intelligence [19],[20], specifically from a group of knowledge elicitation methods described by the common term real-time Delphi [6], where experts reply to structured questions, and the knowledge thus gathered is verified, fused, further processed, and merged with knowledge from other sources. This is the typical approach used in complex decision making and foresight studies. We will explore the idea that any kind of information source in a GES can be dealt with in a similar manner to experts in a Delphi, while Delphi-specific mechanisms that limit the number of knowledge elicitation steps can be adopted and used to define the stopping criteria for information processing in GES.

A fundamental assumption is that problem solving using a GES should be an anytime process [3], monotonic with respect to the number of information sources taken into account and to the complexity of analytic procedures. In Sec.3 we will formulate the hypothesis that due to the high and ever-growing level of interconnection of knowledge sources, sensors, processing units, knowledge bases and repositories, a universal intelligence emerges, which under certain conditions can outperform the intelligence and creativity of any of its individual elements, including humans. It will be shown that this is possible only if an appropriate level of credibility can be assigned to each element of the system in order to ensure a certain level of trust in the system outputs on part of its users.

Trust and credibility management turns out to be the first main issue that can hinder or allow the use of heterogeneous knowledge repositories and their interconnected systems as a GES. A basic principle related to trust management, presented below, is the distinction between trust in an individual knowledge source and the credibility of information received from it. This corresponds to a well-known fact that a distrusted source of information that has a high probability of providing false responses can nevertheless be a useful source of information provided that a lower probability is assigned to the actual response of this unit than to its complementary statement.

The second relevant issue that needs to be considered when designing a GES is the choice of a search-and-survey strategy to process a query reviewing a very large number of feasible information sources. The survey planning approach, presented e.g. in

[14], cannot be used in a dynamically changing environment with a very large number of potential knowledge sources, out of which only a quotient is explicitly known *ex-ante*. Also, classical precision-and-reward assessment of responses to the query will fail for a number of reasons. In particular, the user will not be able to assess the results on his/her own and will be forced to delegate the judgment regarding the quality of the reply and corresponding decisions to autonomous agents. A heuristic search-and-survey procedure can be designed making use of the *creative decision process* notion [15], where the user defines an initial subset of information sources according to some criteria, assigns them trust coefficients and activates the procedure that runs recursively at each information source, transforming them to autonomous agents with similar capabilities as the user. This allows the search to be pursued by these agents in a deeper web autonomously and simultaneously, up to a prescribed stack level. Assuming that at each level N information sources on average can be specified for the next-step search, and that the procedure prevents retrieving information from any site two or more times in one run, we obtain $N(N^K-1)/(N-1)$ information sources that can be surveyed in K steps, a sufficiently large quantity when compared with the number of websites ($\sim 10^9$) in existence nowadays.

In Sec. 2 we will design a hybrid supervised-reinforced learning scheme that can assist in achieving a satisfactory level of trust in GES responses. We will also apply knowledge fusion methods [16], including the anticipatory networks [17], Ashton [1], and Hogarth [7] approaches to combine qualitative recommendations and forecast combination methods preserving different optimality criteria [2],[4]. In Sec.3 we will show the synergy of the above fusion and trust models in an emerging GES. Sec.4. presents a real-life example related to trust management in an IT foresight exercise.

2 Trust management in a GES

The main purpose of using a trust and credibility management model in a GES can be presented as follows. We have claimed that a query response from a GES endowed with a suitably designed trust management functionality can outperform a response provided by the same GES acting on a subcomponent of its knowledge base in terms of expected *ex-ante* return information value. This is another formulation of the any-time property with respect to knowledge resources used. It prevents the well-known threat of spoiling credible information by merging it with additional unverified data. The value of the return information is to be defined as a performance index related to the benefits from the further use of this information [14] by the recipient of the response. If the response is quantitative, its value is usually a monotonic function of the accuracy that can be measured *ex-ante* as the standard deviation from the expected value.

The desired properties of the GES are achieved due to the action of intelligent algorithms capable of fusing the knowledge gathered from individual sources, taking into account different competence levels and different degrees of credibility among various types of information sources. The instances of the latter, when regarded as elements of a GES, will be termed here *knowledge units* (KU). We will assume that an agent that generates the query and receives the response is a knowledge unit as well, i.e. the refined knowledge gathered by this agent can be retrieved later by other KUs. Such an agent will be termed an *active knowledge unit* (AKU), as long as the knowledge management system of the GES is activated by this agent.

The credibility of each KU is modelled by a vector whose coordinates correspond to each subject area in a query that is independent from the other areas. This vector describes the ability to provide correct answers in the areas of interest. In addition, trust coefficients describe the KU's ability to provide genuine answers, based on full knowledge resources. Observe that these assumptions differ from the most widespread Dempster-Shafer-based trust and confidence models [5],[8],[11] as well as from the rough-sets-based credibility model [13]. This is justified by the way the trust and credibility coefficients are updated in our model using the reinforcement learning scheme that better fits an update of a single coefficient of a KU at one time than an update of three or four belief/disbelief/uncertainty measures. Another justification of using single trust coefficients comes from the way they are further used to combine recommendations and forecasts, where the aggregate value is a linear combination of individual statements. Nevertheless, it is expected that our approaches would lead to similar results as the other two mentioned above, as the mutual monotonicity of coefficients used in these approaches is preserved by iterative update rules.

Once substantial credibility and trustworthiness has been described numerically, an aggregation function may be used to fuse the information from different KUs, using the maximum likelihood principle, similar to combining recommendations or forecasts [1],[2]. If the estimated distribution has several maxima or if its variance exceeds a certain threshold, then the survey outputs are clustered and a prescribed number of scenarios is produced using the Bates and Granger [2] method to combine forecasts based on the maximum likelihood principle [6]. The credibility vectors and trust coefficients will be updated recursively, taking into account the updates caused by one's responses in other opinions. The learning scheme applies supervisory or weak supervisory learning models that can be implemented as a hybrid neural network with generalised neurons that model KUs. This model can be used to manage the credibility of all KUs and heterogeneous sources of information such as experts, experts systems, sensors, web databases, books, articles etc. within a knowledge building process.

The neural supervised learning model will be applied to update credibility vectors assigned to different sources of information, while moderated self-assessment is used to define the initial values. We will distinguish between trust in the information source and credibility of a particular instance of information produced by this source. The latter may be low even though we trust the source of the information which claims to be unsure of the query issue. Response errors detected *ex-post* by a supervisor will be quantified for qualitative replies as well and transformed into increments (or decrements) of the credibility vector. Such quantification requires a definition of a proximity measure over all potential qualitative responses. This results in a combined trust-credibility model which can be applied in a GES emerging from a large number of heterogeneous interconnected databases.

The fundamental assumption of credibility management for a GES is that a coefficient $c_{ij} \in [-1,1]$, termed credibility of the i-th KU in the j-th subject area, can be assigned to each KU that belongs to the GES. For a fixed i, the coefficients c_{ij} form the competence vector C_i corresponding to the i-th KU. Then C_i are used as coefficients of the aggregation functions that merge the responses to the query provided by the individual KU. The values of C_i that yield minimal error are sought.

Initial values of C_i can be defined in various ways, based on the initial assessments by the user, on the self-assessments of the expert KUs, as well as possibly resulting from earlier searches. If the supervised learning scheme can be applied to credibility management and to optimize the trustworthiness of the query responses at an AKU then the information processing by a GES can be organized analogously to a two-round Delphi exercise [10], as follows:

Procedure 1.

Step 1. The criteria to select the KU are defined by the AKU as well as criteria to transform a KU to the next-level AKU.
Initial credibility coefficients are assigned to all KUs in the subject areas of the present and subsequent queries.

Step 2. KUs respond to the queries, either qualitatively (multiple choice replies selected from the user-defined list) or quantitatively (numbers, functions etc.), provide justifications, and feed them to the AKU.

Step 3. The AKU, possibly assisted by experts, reviews the responses and modifies the KU trust coefficients based on the knowledge supplied by all experts.

Step 4. The AKU assisted by an expert panel clusters the 2^{nd} round replies and – based on this AKU's choice criteria - selects either
- a consensus, which ends the procedure by skipping to Step 6,
or
- accepts a dissensus by defining a number of plausible reply scenarios, the procedure goes to Step 6,
or
- defines further AKUs from among KUs to pursue the search; the present process becomes idle until the next-level search results are obtained.

Step 5. The next-level AKUs are activated unless the *K*-th search level or a time constraint is reached, in the latter case go to Step 6.

Step 6. The final results are presented to the higher-level AKU (for K>1) or to the user (for K=1).

The experts in Steps 3 and 4 can be either human experts assisting the user or autonomous agents that store the results of earlier searches by different users and are able to modify the trust coefficients and clustering criteria. At a search level greater than *1* they may also define the KU's selection criteria for next-level search. The autonomous agents can be provided as the service of a web company, for instance by the operator of a search engine or independent companies. They will be termed *knowledge recommenders.*

So far we have made no assumption about the structure of the query. Now let us assume that the AKU processes a complex query consisting of *J* questions that are replied by *M* different KUs. The responses can be either numerical or may belong to a finite set of attributes. The learning principle used to update the KU credibility vectors within the 2^{nd} round of query processing at an AKU can now be formulated as

$$\hat{c}_{ij} := s(c_{ij} + \sum_{k=1}^{M} c_{kj}\delta_{kj}(r_{ij}, r_{kj}, \hat{r}_{kj})) \tag{1}$$

where c_{ij} is the credibility of the i-th KU in the j-th area, r_{ij} is the first round reply of the i-th KU to the j-th question, $\hat{r}_{kj}$ is the k-th KU reply to the j-th question in the 2^{nd} round, updated after knowing all 1^{st} round replies and the supplementary justification material (if any). Further, δ_{kj} are functions transforming the value of the change of the k-th KU response to the j-th question influenced by another (e.g. i-th) KU response in the 1^{st} round. The threshold function that maps $\mathbb{R}$ monotonically in $[-1,1]$ may be defined as

$$s(x)=x \text{ iff } x\in[-1,1] \text{ else if } |x|>1 \text{ then } s(x)=sgn(x). \tag{2}$$

Alternatively, a sigmoid transformation may be used. We assume that the initial values of c_{ij} are always non-negative. Trust coefficients c_{0i} are updated similarly to (1) based on contradictory statements in the responses and the deviations between the self-assessment of credibility in an area and the quality of justifications assessed by 2^{nd} round experts. They may be used as additional adjustment coefficients in (1).

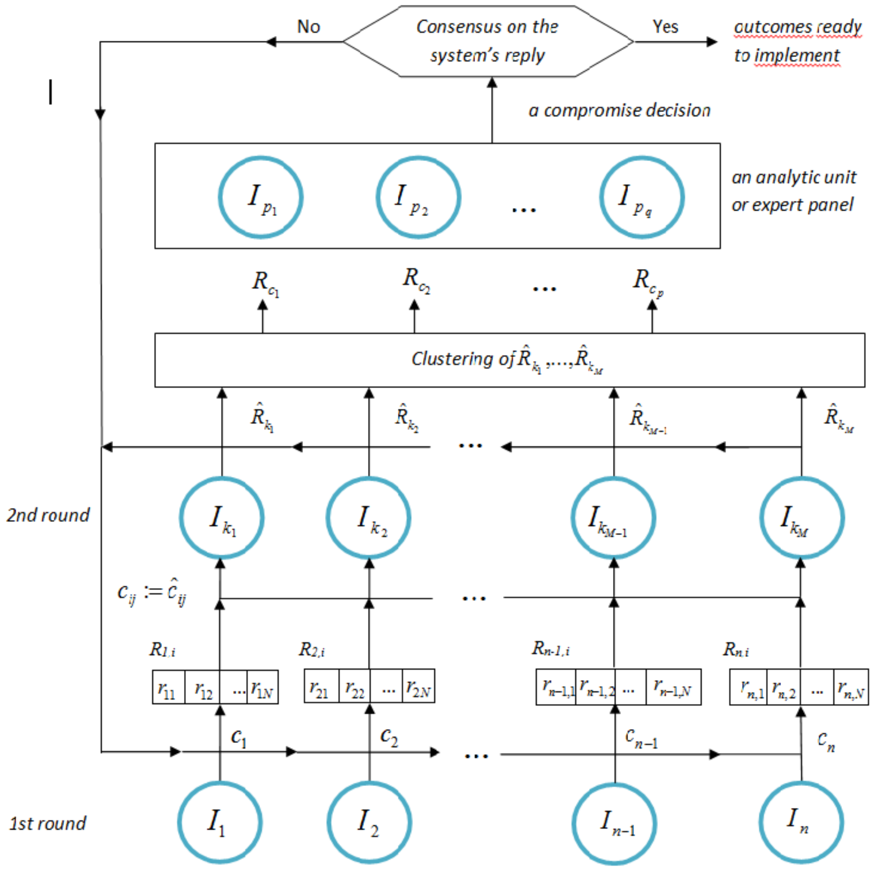

Fig. 1. A scheme of supervised learning applied to the trust coefficients $c_1,\ldots,c_n$ of information sources $I_1,\ldots,I_n$. in a GES.

The δ_{kj} are to be selected in such a manner so that the optimization problem

$$\sum_{p=1}^{P}\sum_{i=1}^{n(p)} (r_{cpj}(\hat{c}_{1j},...,\hat{c}_{nj}) - r_{ij})^2 \rightarrow \min, \quad \mathit{for}\ j = 1,...,N \tag{3}$$

where r_{cpj} are p-th scenario values of the j-th reply after clustering, $p=1,\ldots P$, and $n(p)$ is the cardinality of the p-th cluster. The inner summation is performed over the responses that were assigned to the p-th cluster.

Let us note that (2) is in fact a bi-level multicriteria optimization problem, where the optimality of c_{ij} in (2) depends on a prior finding of the optimal δ_{kj} in (1). If the number of scenarios P is not a priori given then P becomes additional variable to be optimized in (2). If $P=1$ then (2) reduces to a consensus finding problem. The above procedure is shown in Fig.1.

3 An application of the fusion of expert information and quantitative trend models

The knowledge processing scheme applying the credibility and trust of experts interacting in a structured way and other knowledge units selected from a plethora of potentially useful information sources turned out useful in designing the Delphi exercise in a foresight project on the Information Society technologies carried out recently [13]. Many other recent foresight exercises (cf. e.g. [6]) use computer-assisted Delphi questionnaire research as one of their knowledge acquisition tools. In [18] the same trust-management scheme has been applied to define the information retrieval strategy from the open web and from the bibliographic databases. Finally, the scheme presented in Sec.2 has been used in information fusion algorithms. Different procedures to combine knowledge and forecasts and to generate recommendations to the decision-maker have been elaborated from the knowledge gathered.

One of the main problems that arise when analysing Delphi research outputs is the diversified trustworthiness of individual respondents who may possess different qualifications, expertise, and access to information and modelling tools. In addition, experts' responses may be burdened by a tendency to present views that coincide with individual gains rather than provide an objective picture. This problem is especially relevant where the research covers a large multi- or interdisciplinary area, when it is difficult to find an expert in all areas simultaneously. A similar problem arises when there is a need to involve different groups of practitioners, students and stakeholders, which may provide information with varying degrees of trustworthiness in specific or all areas, or if the exercise uses crowdsourcing.

The credibility of each expert has been modelled by a vector whose coordinates correspond to each of the following areas in the Delphi questionnaires:

- the economic and social aspects of Information Society development
- e-commerce, e-government, and e-business
- decision support systems and recommenders
- diagnostic and embedded expert systems
- computer vision
- robotics and autonomous intelligent systems

- neurocognitive systems
- molecular computing
- quantum computing.

This vector describes the ability to provide correct answers in the areas covered by the survey. In addition, trust coefficients describe the participants' ability to provide genuine answers. To apply Procedure 1 to analyse the outputs of an expert Delphi consisting of responding to structured questionnaires on IT development trends, we have to define the initial trust coefficients as presented in Tab.1 below.

Table 1. The assignment of initial competence scores to experts (self-assessment)

Verbal Self-Assessment of Competence in a Survey Area	Verbal Self-Assessment of Practical Skills in an Area	Numerical value	Normalised score
I am not interested in this issue (the question may be skipped)	I have no experience with these methods/topics	1	0/0,05 (0 if no reply)
I only have some general know-ledge in this area (but I shall try to fill in the questionnaire)	I know some articles reporting the practical experience in this area or I use these methods sporadically	2	0,25
I feel confident with some of the issues in this area	I have been regularly using so-me of these methods / applica-tions	3	0,5
I am confident with all the relevant issues in this area	I am an experienced user of most of these methods and tools	4	0,8
I am a specialist in this area	I am a specialist-practitioner	5	1

The numerical coefficients input to Procedure 1 have been calculated as products of normalised scores and initial trust coefficients, for each subject area separately. Once substantial credibility and trustworthiness have been described numerically, the expected *ex-ante* error of the combined output can be calculated using e.g. the approa-ches presented in [1] or [4]. The ultimate goal of selecting the most appropriate trust and credibility coefficients was to minimise this error. If the estimated distribution has several maxima or if its variance exceeds a certain threshold, then the survey outputs are clustered and a prescribed number of scenarios is produced based on the maxi-mum likelihood principle. During the analysis of results, the credibility vectors and trust coefficients are updated recursively, taking into account the updates caused by the assessments of responses of the Delphi participants by the core expert group. The opinions of other respondents of the same exercise can also be taken into account as well as the contradictions in the responses that can be detected automatically. The learning scheme applies neural network supervisory learning models.

Further analysis may eventually lead to defining bibliographic sources to comple-ment the missing or incomplete expert responses, using the recursive *k*-th to *(k+1)*-information source level transition scheme presented in Sec.2. Multi-round Delphi studies can be dealt with within a similar framework. The combination of the *ex-ante* error analysis with the usual *ex-post* approaches could convert the semi-supervised trust learning scheme to a supervised scheme as soon as the verification of foresight results derived from Delphi are possible, usually only after a long time lapse. A further discussion of this approach, and its results in IST foresight, is given in [18].

4 Discussion and conclusions

The research on the credibility of experts in a Delphi exercise has been first extended to deal with credibility and trust in group model building systems aimed at elaborating complex socio-economic evolution models [16]. Then, the common expert reputation management system has been used for several analytic engines to optimize the choice of experts to taking part in particular exercises from the point of view of simultaneously maximising the probability of judgments and the statistical trustworthiness of outputs [19]. Further application of decision-making creativity in a GES framework, according to the notion presented in [15], will allow us to enhance the autonomy of the knowledge gathering process in Delphi exercises by the automatic search for web, patent, and bibliographic information, as well as to request opinions of additional experts.

Creativity in a GES has at least a twofold meaning: it can be artificial creativity (delegating complicated search strategy selection tasks to autonomous agents) as well as creativity of users aided by intelligent agents. Furthermore, it can be expected that the opinion dynamics and their distribution within the same group of experts can be forecasted using the state-space model and Kalman filtering as proposed in [11].

An important feature of the recursive search procedure and judgment fusion algorithms proposed above is its universality. Specifically, the GES framework will allows users to manage trust, confidence, and credibility of heterogeneous sources of information, such as experts, expert systems, web databases, books and articles etc., in a uniform way. Even unattainable information sources (e.g. absent experts) can be assigned credibility vectors and trust coefficients, using the Kalman filter in a similar way as proposed above. Queries related to the future can be modelled and replied to within an anticipatory networks framework [17] coupled with forecasting models such as the Kalman filter or VARIMA [12].

Another challenging problem is the evolution of the system of semi-autonomous agents that perform a knowledge search in a future heterogeneous web. They can be termed semi-autonomous because they get task from higher-level agents, but the way the tasks are fulfilled can be chosen autonomously. It can be conjectured that such agents show a self-organisation behaviour similarly to the interacting brain regions considered in [9]. If a brain-like hierarchy can be followed by artificial structures of very different origin and nature, driven only by the similarity of evolutionary mechanisms, the consequences might be amazing: a spontaneous emergence of a super brain in large artificial networks, without any biological limitations, and potentially able to produce brain-like states.

Acknowledgement. The results presented in this paper have been obtained during the research project “Scenarios and Development Trends of Selected Information Society Technologies until 2025” financed by the ERDF within the Innovative Economy Operational Program 2006-2013, Contract No. WND-POIG.01.01.01-00-021/09.

References

1. Ashton, A.H, Ashton, R.H.: Aggregating subjective forecasts: Some empirical results. Management Science, 31, 1499-1508 (1985)
2. Bates, I J.M., Granger, C. W. J.: The combination of forecasts, Operational Research Quarterly, 20, 451-468 (1969)
3. Dean, T.L., Boddy, M.: An analysis of time-dependent planning. In: Proceedings of the Seventh National Conference on Artificial Intelligence AAAI-98, St. Paul, MN, pp. 49-54. (1988)
4. Elliott, G., Timmermann, A.: Optimal forecast combinations under general loss functions and forecast error distributions. Journal of Econometrics 122, 47--79 (2004)
5. Gligor, V., Wing, J.M.: Towards a Theory of Trust in Networks of Humans and Computers. Lecture Notes in Computer Science, 7114, Security Protocols XIX, pp. 223-242 (2011)
6. Gnatzy, T., Warth, J., von der Gracht, H., Darkow, I.-L.: Validating an innovative real-time Delphi approach - A methodological comparison between real-time and conventional Delphi studies. Technological Forecasting & Social Change, 78, 1681--1694 (2011)
7. Hogarth, R.: A note on aggregating opinions, Organizational Behavior and Human Performance, 21, 40--46 (1978)
8. Jøsang, A.: A Logic for Uncertain Probabilities. Int. J. Uncertainty, Fuzziness Knowl.-Based Syst., 9(3), 279--311 (2001)
9. Joyce, K.E, Laurienti, P.J.; Hayasaka, S.: Complexity in a brain-inspired agent-based model. Neural Networks, 33, 275--290 (2012)
10. Linstone, H.A., Turoff, M. (eds.): The Delphi Method. Techniques and Applications. Electronic version © Harold A. Linstone, Murray Turoff, p. 616 (2002)
11. Moyano, F., Fernandez-Gago, C., Lopez, J.: A Conceptual Framework for Trust Models, Trust, Privacy and Security in Digital Business, Lecture Notes in Computer Science, 7449, pp. 93-104. Springer-Verlag, Berlin-Heidelberg (2012)
12. Öller, L.E.: Macroeconomic forecasting with a vector arima model ☆: A case study of the finnish economy. International Journal of Forecasting, 1(2), 143--150 (1985)
13. Podraza, R.: Credibility Coefficients in Hybrid Artificial Intelligence Systems. In: E. Corchado et al. (Eds.): Hybrid Artificial Intelligence Systems, 4th International Conference, Salamanca (HAIS 2009), LNAI, 5572, Springer-Verlag, Berlin-Heidelberg, pp. 187--194. (2009)
14. Skulimowski, A.M.J.: Optimal strategies for quantitative data retrieval in distributed database systems. Proceedings of the Second International Conference on Intelligent Systems Engineering, Hamburg, 5-9 September 1994; IEE Conference Publication Nr 395, IEE, London; pp. 389--394 (1994)
15. Skulimowski, A.M.J.: Freedom of Choice and Creativity in Multicriteria Decision Making. In: T. Theeramunkong, S. Kunifuji, C. Nattee, V. Sornlertlamvanich (Eds.) Knowledge, Information, and Creativity Support Systems: KICSS2010 Revised Selected Papers, LNAI, Vol. 6746, Springer, Berlin; Heidelberg (2011), pp. 190--203
16. Skulimowski, A.M.J.: Discovering Complex System Dynamics with Intelligent Data Retrieval Tools. In: Zhang, Y. et al. (eds.): Sino-foreign-interchange workshop on Intelligent Science and Intelligent Data Engineering IScIDE 2011, Xi'an, China, Oct. 23-26, 2011, Lecture Notes in Computer Science, 7202, Springer, Berlin–Heidelberg, pp. 614--626 (2012)
17. Skulimowski, A.M.J.: Anticipatory Network Models of Multicriteria Decision-Making Processes. Int. J. Systems Sci., 44, iFirst (2012) DOI:10.1080/00207721.2012.670308
18. Skulimowski, A.M.J. (ed.): "Scenarios and Development Trends of Selected Information Society Technologies until 2025" Final Report, Progress & Business Publishers, Kraków, Progress & Business Foundation, available at http://www.ict.foresight.pl (2013)
19. Tapscott, D., Williams, A. D.: Wikinomics: How Mass Collaboration Changes Everything, 3rd Ed., Portfolio Trade (2010)

20. Tovey, M. (Ed.): Collective Intelligence: Creating a Prosperous World at Peace. Earth Intelligence Network, Oakton, VA (2008)
21. http://en.wikipedia.org/wiki/Exabyte [accessed Oct.15, 2012]