Transforming Implicit to Explicit Knowledge in Economics – The case of Novel Adsorbents Production within an Industrial Ecology Framework

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Abstract**—** This work deals with transforming implicit to explicit knowledge in techno-economic issues with emphasis on cost-benefit analysis supporting optimization techniques. Initially, the minimization of the Cost to Acquire all the Explicit Knowledge (CAEK), needed to do a prescribed job, is introduced as an economic optimization criterion. The main difficulties appearing in such an optimization process are noted and an algorithmic procedure is presented as an aid for solving such problems. Subsequently, the case of a novel lignocellulosic adsorbent production is analyzed as an implementation paradigm taking place within an Industrial Ecology framework, where waste lignocellulosic materials and thermal energy are used to give a product suitable for environmental protection. Next, the economic subsidy required to support such an investment is determined with a new economic approach, based on non-monotonic function used to estimate benefits (resulting from materials/energy saving/substitution, sustainable regional development, and environmental risk decrease), in the time course. Last, the exploration/amelioration of this product is examined, putting emphasis on the R&D aspect, always from a techno-economic point of view, where the cost of required examination/measurements of raw/intermediate/final materials and the benefit from quality improvement are the principal conflict variables in the respective tradeoff technique adopted herein, with the corresponding information granularity level representing the independent explanatory variable to be optimized.

Keywords**—** cost–benefit analysis, environmental protection, implicit–explicit knowledge, industrial ecology, materials R&D.

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I INTRODUCTORY ANALYSIS

The Implicit to Explicit Knowledge Transformation (IEKT) can be considered as part of Nonaka’s SECI model [1], as modified in [2], [3], including the following four procedural stages: (i) Socialization (S), as the process of converting shared experience into new tacit/implicit knowledge; (ii) Externalization (E), as the process of articulating tacit/implicit knowledge into explicit knowledge either by hypotheses making, to be subsequently tested under real or simulated conditions, or by simple prototypes preparing, to be subsequently examined for further improvement; (iii) Combination (C), as the process of converting basic/modular knowledge into more complex and systematic sets of explicit knowledge, including hypotheses (made in the immediately previous stage, E) testing and dissemination/diffusion at a formal/agreed level; (iv) Internalization (I), as the process of embodying explicit into tacit/implicit knowledge by individuals involved, mainly through ‘learning by doing’/ observing and sharing formal knowledge.

One of the main weaknesses of the original SECI model, is the lack of optimization mechanism, since the sequence of the four processes/stages is presented to occur like a physical phenomenon (i.e., without rational/normative guidance). From an economic point of view, the realization of the E-C path might never take place if the cost of adopting a computer aided expert system, giving the same results as regards the undertaken job, is significantly less in comparison with the estimated E-C cost, in the Nonaka's modified model.

The minimization of the Cost to Acquire all the Explicit Knowledge (CAEK) needed to do the prescribed job can be used as an optimization criterion by splitting the CAEK objective function C(R) into two conflict variables $C_1(R)$ and $C_2(R)$, where $C_1(R)$ is the IEKT cost, $C_2(R)$ is the cost to purchase/operate/maintain/update the rest explicit knowledge to the extent/depth required to complete the CAEK, and R is IEKT ratio, expressed as the percentage (%) of the implicit knowledge already transformed.

The partial cost C_1 is an increasing function of R, with an increasing rate (i.e., $dC_1/dR>0$, $d^2C_1/dR^2>0$), because of the validity of the Law of Diminishing (differential or marginal) Returns (LDR): effort and resources consumption is disproportionally higher as R increases. On the other hand, the partial cost C_2 is a decreasing function of R with an increasing algebraic or a decreasing absolute rate (i.e., $dC_2/dR<0$, $d^2C_2/dR^2>0$ or $d|dC_2/dR|/dR<0$), because the higher the R value, the lower the extent/depth of the explicit knowledge required for purchasing (including operation/maintenance); this is a convex non-linear function, since information and know-how at lower granularity level is less effort and resources consumption demanding and finally less expensive in market prices (also in accordance with the LDR). Evidently, R_{opt} is the abscissa of the equilibrium point in the tradeoff between C_1 and C_2, where the economic optimization criterion $C_{min}=(C_1+C_2)_{min}$ is fulfilled; at this point, $dC/dR=0$ or $MC_1=MC_2$, where $MC_1= dC_1/dR$ and $MC_2=|dC_2/dR|$ are marginal costs of C_1 and C_2, respectively.

In case that a computer based Expert System (ES) is introduced to support IEKT (by decreasing the corresponding partial cost), the C_1-curve is expected to move downwards to a new position C_1', becoming also more flat; the impact of the ES introduction will be more expressed in the region of high R-values, implying the shift of R_{opt} to R'_{opt}, where $R'_{opt}>R_{opt}$, as shown in Fig. 1a. If another ES, based on fuzzy logic and uncertainty analysis, is introduced to facilitate the I-S path in the modified Nonaka's model, the C_2-curve is expected to move downwards to a new position C_2', becoming also more flat, since this introduction will be more expressed in the region of lower R-values, where tacit/implicit knowledge is dominant; as a result, R_{opt} is shifting to R''_{opt}, where $R''_{opt}<R_{opt}$, as shown in Fig. 1b.

It is worthwhile noting that, in both cases examined above, the optimal value C_{min} is moving downwards, while the vectors $(R'_{opt}-R_{opt})$ and $(R''_{opt}-R_{opt})$ have opposite direction, implying that the final position of the R_{opt} (i.e., to the left or right of the original value) will depend on the form of the partial cost functions and their parameter values. It is also important, from a formalistic point of view, that the tradeoff analysis between implicit and explicit knowledge has several common points with decision making in Production Logistics, especially when the question 'to buy or to make it' has to be answered (mostly interesting when recyclable materials are

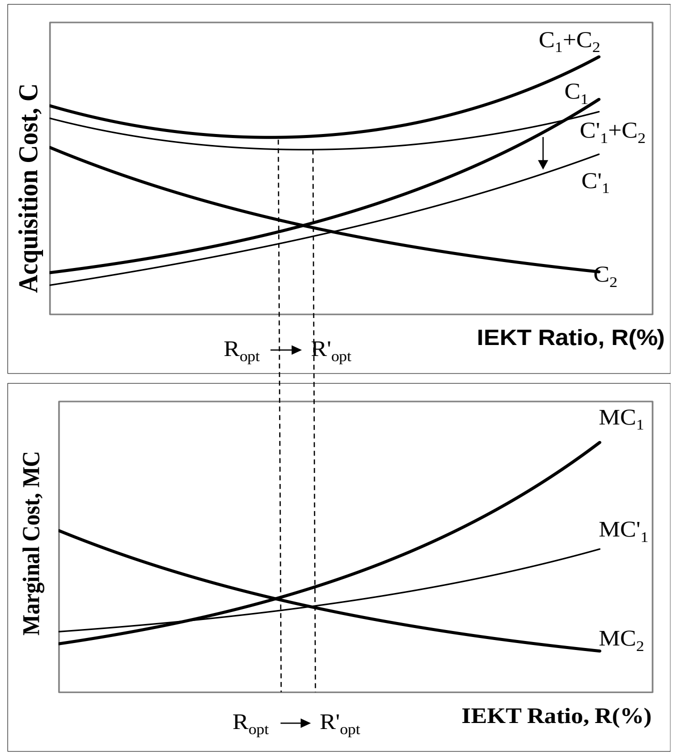

Fig. 1a Dependence of partial costs C_1 and C_2 on the Implicit to Explicit Knowledge Transformation (IEKT) Ratio, R, and shifting of R_{opt} to the right, when an ES is introduced to support this transformation, implying downward movement of C_1 to C_1'.

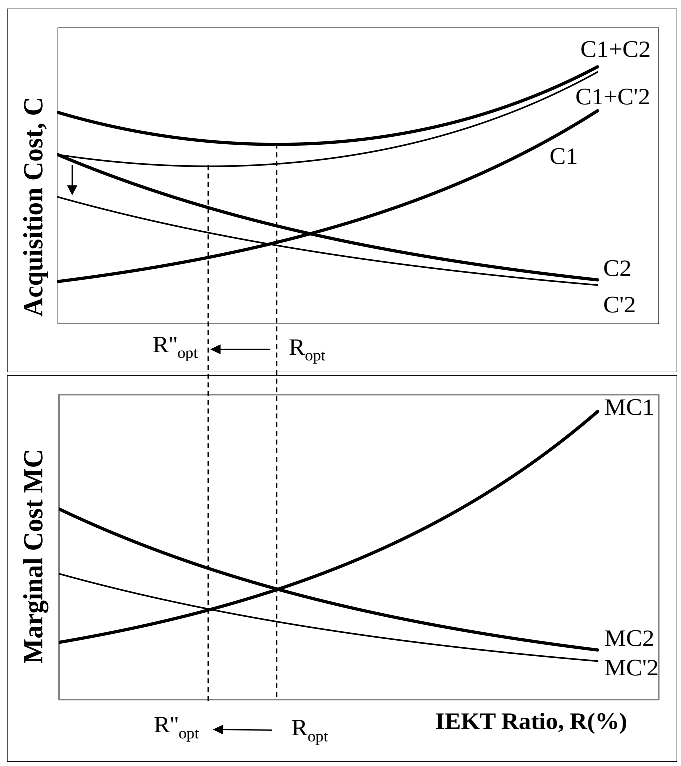

Fig. 1b Dependence of partial costs C_1 and C_2 on the Implicit to Explicit Knowledge Transformation (IEKT) Ratio, R, and shifting of R_{opt} to the left, when an ES is introduced for facilitating purchase/ operation/maintenance/updating of the explicit knowledge that remains to be acquired from external KBs.

considered, since their fate after the end-use should be designed *a priori,* according to Life Cycle Analysis/Assessment – LCA).

As a matter of fact, the problem of estimating the R_{opt} value is more complicated in comparison with the conceptual tradeoff described above, because of the following factors: (i) At micro-economic level, the IEKT cost will depend on the type of the Inference Engine (IE) adopted to function within the internal Knowledge Base (KB) and the external KBs, as well as on the existence/availability/ enrichment of the latter; (ii) At macro-economic level, both C_1 and C_2 costs depend on the economic support given by the State or the Local Authorities under the form of subsidies; (iii) At medium-economic or regional level, the IEKT cost will depend on the attitude of stakeholders, especially when the target population is a traditional one; (iv) The partial cost functions C_1 and C_2 are actually, at least to some extent, depended to each other, mainly through a demand-supply interactive mechanism.

II METHODOLOGY

For solving the problem mentioned above, we have designed/developed a methodological framework under the form of an algorithmic procedure with the following 26 activity stages and 8 decision nodes, interconnected as shown in Fig. 2.

1. Definition of the problem with emphasis on the kind of implicit knowledge that should be transformed into explicit knowledge.
2. Setting of economic, technical, and environmental limitations and constraints in the domain under consideration.
3. Determination of the model to be used and identification of its economic/technical/environmental parameters, mostly representing implicit/subjective knowledge.
4. Definition of the boundaries set by the wider theoretical and practical approaches, as well as by national/EU legislation and standards or recommended practices.
5. Assignment of proper values on the parameters identified in stage 3, in interval or fuzzy form in order to (i) count for uncertainty and (ii) facilitate consensus in the group decision making by the experts.
6. Sensitivity analysis of the proposal made by the experts either under the form of unique solution or as various alternatives.
7. Robustness analysis in relation with the same parameters.
8. Partition of each parameter domain, according to a Likert-type scale and synthesis of the required fuzzy rules.
9. Data acquisition/entry in proper fuzzy version, in accordance with the partition mentioned above.
10. Selection and multicriteria ranking of the methods suggested to be used if consensus in input is adopted.
11. Performance of fuzzy calculations in input.
12. Selection and multicriteria ranking of the methods suggested to be used if consensus in output is adopted.
13. Performance of fuzzy calculations in process/output.

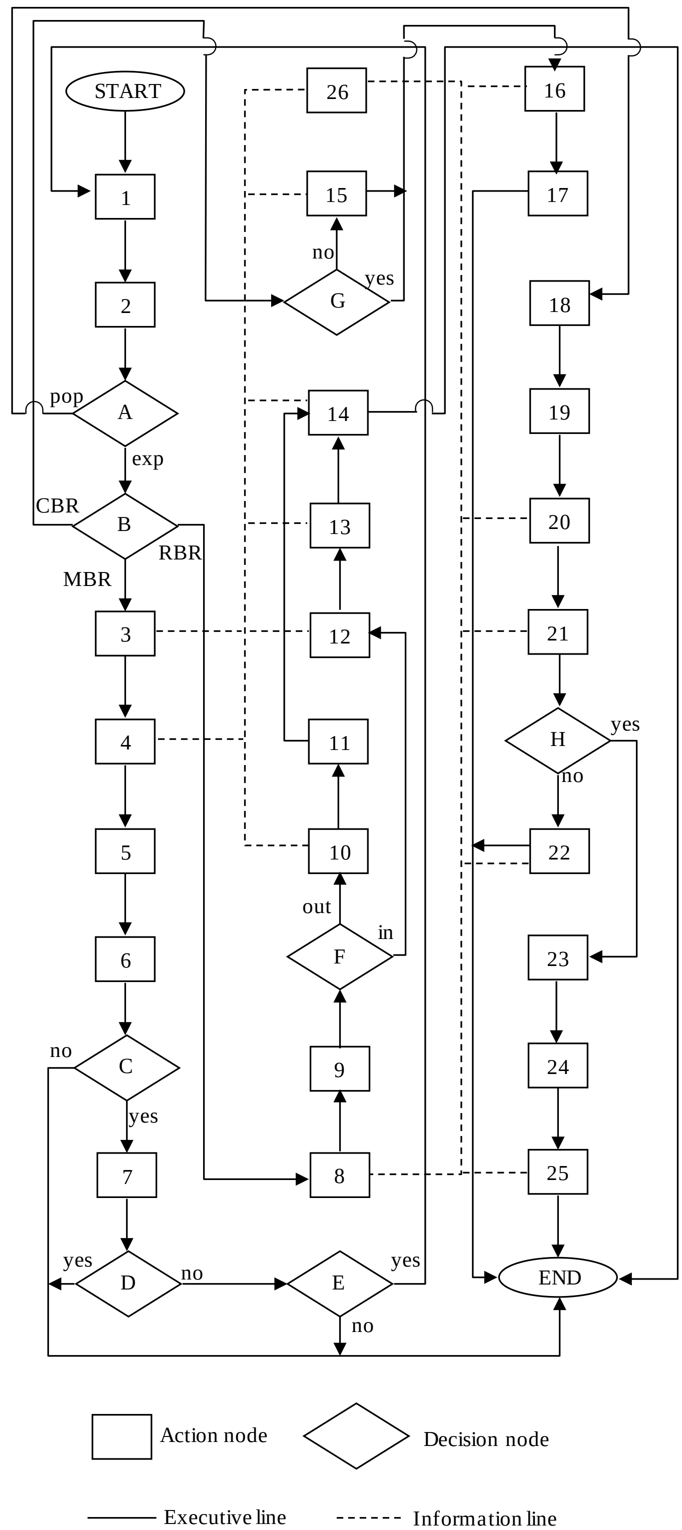

Figure 2. Flowchart of the algorithmic procedure developed as an aid to quantify the factors involved in the determination of the IEKT function.

14. Evaluation of results.
15. Knowledge discovery/transfer in/from external sources by means of an IA interfacing with the internal KB [4].
16. Multicriteria choice of the most relevant case among the selected ones.

17. Mapping of the solution from the chosen (as the pilot paradigm) past case to the problem defined in stages 1,2, and execution of the necessary cases.
18. Preparation of a preliminary questionnaire and circulation in a properly stratified sample of the target population.
19. Processing of response and synthesis/circulation of the final complete questionnaire.
20. Computer aided processing of answers to obtain partial correlations and combined conclusions.
21. Comparison of these conclusions with results reported by other researchers, who have solved similar problems with the same or different methods of Experimental Economics, thus performing meta-analysis by ‘conducting research about previous research’.
22. Final conclusions enriched with the meta-analysis results.
23. Synthesis of a new questionnaire by taking into account the ‘weak points’ determined/identified by means of meta-analysis.
24. Circulation of the new questionnaire within the same target population and processing of response.
25. Comparison of results with those obtained in stage 20 and final conclusions.
26. Design/development of procedures to obtain the required additional knowledge and development/ operation/updating of the internal KB.

A. Will this transformation be performed indirectly by the aid of human experts or directly by means of ‘Experimental Economics’ methods (like the Contingent Valuation Method – CVM), denoted with ‘exp’ and ‘pop’ in the corresponding decision node, respectively, as shown in the flowchart of Fig. 2?
B. Is the Inference Engine (IE) to be followed by the experts in accordance with Model/Rule/Case Based Reasoning (denoted by MBR, RBR, CBR, in the corresponding decision node, respectively, as shown in the flowchart of Fig. 2)?
C. Is the best solution (i.e., the unique or the ranked first in case of alternatives) sensitive within the boundaries quoted in stage 4?
D. Might the best solution (found in stage 5 and examined for sensitivity in stage 6) characterized as a robust one, according to the experts’ opinion?
E. Is there a tolerance margin allowing for reformulation of the problem?
F. Is consensus taking place in input or in output?
G. Are there relevant cases in the internal KB?
H. Is there a need for meta-analysis to determine/identify weak points in the circulated questionnaire itself?

III IMPLEMENTATION

The transformation of implicit to explicit knowledge about the attitude of groups A and B, extracted from the same population sample, as regards their willingness to participate in waste lignocellulosic biomass collection, with and without an economic motive, was performed by using the questionnaire described above. The group A consisted of farmers/stakeholders (including tenants and owners/lenders of agricultural land); the group B consisted of occasional workers (including emigrant laborers). The question was: “Are you Willing To Participate (WTP, which is equivalent to the similarly abbreviated and frequently used in CVM of Experimental Economics) in agricultural residuals sorting/collection and transportation to the closest transshipment point… (*herein is described the condition*)…?” The numerical results, referring to a stratified sample of 34 individuals living in the prefecture of Karditsa (Central Greece) and working in the agricultural sector, were as follows (expressed in the form of dichotomous classification 2x2 matrix):

i) WTP voluntarily (i.e., without any reward).

	Pos.	Neg.	Total
Group A	3	14	17
Group B	2	15	17
Total	5	29	34

ii) WTP with a reward estimated *a posteriori*, based on sharing a total budget given as a variable subsidy, according to short-term cost-benefit analysis criteria.

	Pos.	Neg.	Total
Group A	8	9	17
Group B	15	2	17
Total	23	11	34

iii) WTP with a reward estimated *a priori*, based on sharing a total budget given as a guaranteed annual subsidy, according to a long-term contract.

	Pos.	Neg.	Total
Group A	16	1	17
Group B	17	0	17
Total	33	1	34

The chi-squared test value (denoted by χ^2 in its simple and y^2 in its corrected, after Yates, version) gave the following results. In case (i), $\chi^2 = 0.23$ and $y^2 = 0.00$, which means that the null hypothesis that both samples belong to the same population (as regards the specific attitude expressed/ represented by the respective Boolean value of the respond) is not rejected, since $0.23<3.84$, where $3.84=c$ is the critical value of χ^2 for one degree of freedom at 0.05 significance level; consequently, the population is not willing to participate in the biomass collection voluntarily. In case (ii), $\chi^2 = 6.58 > c$ and $y^2 = 4.84 > c$, which means that the null hypothesis is rejected at the same significance level (not rejected at 0.01 and rejected at 0.025, but not rejected at this level if the Yates’ correction is adopted); consequently, the individuals belonging to group A are equally divided between ‘yes’ and ‘no’, while the individuals belonging to group B are willing to participate. In case (iii), χ^2 = 1.03 < c and y^2 = 0.00, which means that the null hypothesis is not rejected at the same significance level; consequently, the individuals belonging to both groups are willing to participate.

The transformation of implicit to explicit knowledge can also be achieved by quantifying the experts' opinion within a model including both kinds of knowledge. The co-existence of parameters defined explicitly helps this quantification by providing reference level for total/partial/pairwise comparisons among parameters, increasing the reliability of implicitly defined parameters, especially in procedures making use of exogenous information/knowledge understood/ processed initially implicitly and expressed subsequently explicitly by following the path S-E in the Nonaka's modified model.

Such a case example is the determination of optimal subsidy I_{opt}, as a percentage of the initial investment amount S, according to the following multi-parameter model [5]:

$$I_{opt} = \frac{KF(1+i)^{t-1}\left[[(1+f)/(1+i)]^t - 1\right]}{S(1+r)^t\left[(1+f)/(1+i) - 1\right]} \quad (1)$$

where, K is the fraction of the energy/materials saving and environmental protection (in monetary units) that the State is willing to deduce from its welfare budget, F is the first time period cost savings (increased each period by a fraction f or 100f%), i is the interest rate, t is the number of useful life time periods, and r is the return on the best alternative investment (called 'the second best' in comparison with the first best for the State which is the subsidized fraction I^*S). Evidently, the value of parameter K is endogenously determined implicitly according to experts' opinion, by following the path *S-E* mentioned above, while the value of parameter f is exogenously determined through an Experimental Economics method based on subjective reasoning implicitly.

Understanding the implicit nature of the I_{opt} determination approach, we can change the basic assumption of the model derivation, which gives (as all such models included also in [5]) a monotonic pattern, to achieve non-monotonicity to increase the degrees of freedom of the experts' opinion. For example, if the experts' opinion converges (by deciding either separately, through a Delphi-like method, or collectively/interactively within a group), towards a pattern with a rate of increasing economic/environmental gains initially and decreasing rates subsequently, then a respective model can be derived. Such a model is the following, with the corresponding curve shown on Fig. 3 with inflection point (where the curvature changes) at j=4.258, for r=0.045, K=0.15, b=0.75, t=20, i=0.03, F/S=0.12.

$$I_{opt} = \frac{2KFQ}{S(1+r)^t} \quad (2)$$

$$Q = \sum_{j=0}^{t-1} \frac{(1+i)^{t-1-j}}{1+e^{-bj}} \quad (3)$$

where, the parameter Q gives the pattern of non-monotonic model, and j is the time period.

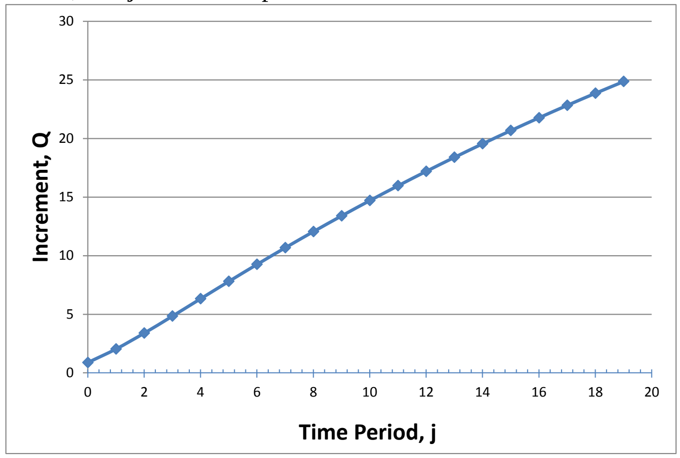

Fig. 3. The dependence of increment Q on time period j, used for determining the optimal subsidy *Iopt*, according to model (2), in combination with expression (3).

The transformation of implicit to explicit knowledge was also implemented by means of a 'parameter identification' technique in the case of the novel lignocellolosic adsorbent developed within our research project. For examining the adsorbent efficiency within an aquatic solution flow through fixed bed, we adopted the empirical sigmoid asymmetric model

$$C = C_\infty / (1 + Ae^{-pt})^m \quad (4)$$

where C is the effluent concentration (the dependent variable), t is the time (the independent variable) and C_∞, A, p, m are parameters. The parameter values can be estimated statistically by performing non-linear regression, for numerical data (t, C) obtained through spectrophotometric measurements and initial guesses obtained by linearizing this model and minimizing the least squares error.

All these parameters are explicit ones, as regards the empirical surface phenomenological level where they belong to. In case that one of them can be analyzed to or considered as a function depended on other parameters that belong to a deeper phenomenological level, we may consider it an implicit parameter as regards the surface level, since at that level the same parameter is a mixture or combination of 'actual' parameters under a unifying denotation or symbolic name. Such a parameter is the m, which can be considered as representing heterogeneity factors, while the parameters C_∞, A, p can be identified by using the Bohart-Adams model [6] to give the following explanatory meaning: $C_\infty = C_i$, where C_i = influent concentration, $A=\exp(KNx/u)$, $r=KC_i$, K = adsorption rate coefficient, N = adsorption capacity coefficient, x = bed depth, u = linear velocity.

Since the parameter m represents combination of thermodynamic factors (giving a measure of heterogeneity or surface/structural disorder leading to energy increase), we can extract it from one of the following isotherms: Freundlich, Toth, Radke-Prausnitz, Redlich-Peterson, Sips. We have adopted this method in [7],[8], by replacing *m* with *1/(n-1)*, extracted from the Freundlich isotherm (following Clark, [9]) where the exponent *1/n* is met, since it is the simplest one among the isotherms mentioned above, according to the principle of simplicity (Occam's Razor). After this replacement, the model fitting to data (examined through the Standard Error of Estimate – SEE) is not equally satisfactory in comparison with the situation before the replacement, especially when the number of measurements is small, since the number of freedom degrees decreases. Nevertheless, this method is successful by offering deeper insight from the physicochemical point of view, partially transforming implicit to explicit knowledge, generalizing also the procedure of entering-enclosing a function within a function, which is the 'hard core' of the modern approach to the parameter identification problem. It is worthwhile noting that we can extend this methodology for modeling an adsorption column for wastewater treatment by using dimensionless groups in scale-up procedures [10].

IV FURTHER INVESTIGATION

A significant part of the transformation of implicit to explicit knowledge is due to operators (serving as personnel in laboratories performing material quality testing) attempt to 'translate' their subjective/tacit to objective/explicit knowledge in order to improve the relevant protocols in accordance with the corresponding experimental design techniques, an ad hoc procedure for which there are not official standard methods or recommended practices, since it is heavily based on each separate case under consideration. The explanatory independent variable that should be optimized is the information granularity level L, while the optimization criterion, serving as the objective function that should be maximized, is the total benefit $B(L) = B_1(L) + B_2(L)$, where the partial benefits B_1 and B_2 depend on uncertainty implications and knowledge acquisition cost, respectively.

The partial benefit B_1 is an increasing function of L with a decreasing rate (i.e., $dB_1/dL>0$, $d^2B_1/dL^2<0$), because of the validity of the technological version of the LDR regarding product quality/reliability as a function of L. The partial benefit B_2 is a decreasing function of L with a decreasing algebraic or increasing absolute rate (i.e., $dB_2/dL<0$, $d^2B_2/dL^2<0$ or $d|dB_2/dL|/dL>0$). As a matter of fact, L_{opt} is the abscissa of the equilibrium point in the tradeoff between B_1 and B_2, where the tecno-economic optimization criterion $B_{max}=(B_1+B_2)_{max}$ is fulfilled; at this point, $MB_1=MB_2$, where $MB_1= dB_1/dL$ and $MB_2= dB_2/dL$ are marginal benefits of B_1 and B_2, respectively.

In case of introducing novel measuring equipment and/or software package, uncertainty is decreased in the region of lower L-values (where uncertainty is already high, implying low reliability/quality), the B_1-curve is expected to move upwards to a new position B_1', becoming also more flat, implying the shift of L_{opt} to L'_{opt}, where $L'_{opt}<L_{opt}$, as shown in Fig. 4a. On the other hand, the cost is expected to increase in the same region, implying the downward movement of the B_2-curve to a new position B''_2, becoming also more flat;

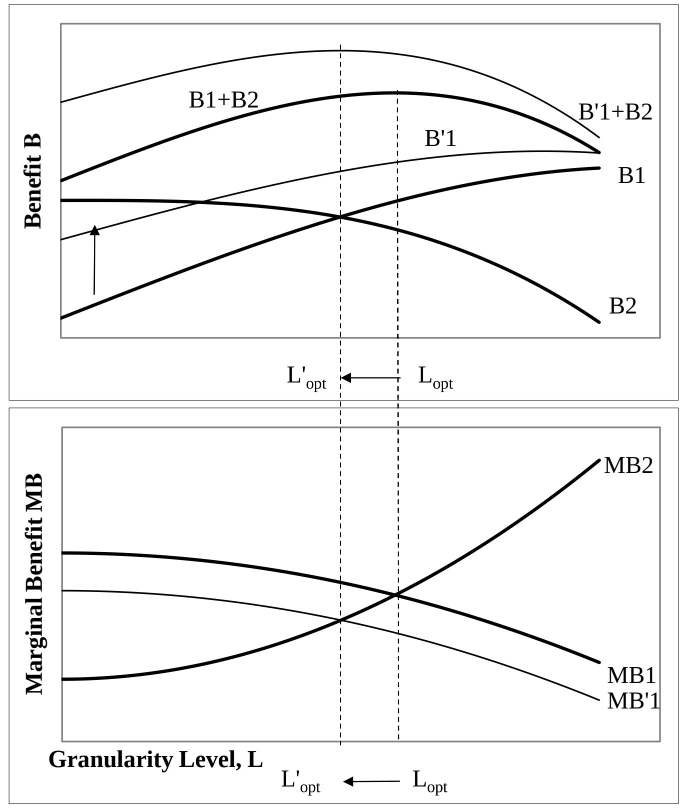

Fig. 4a. Dependence of partial benefits B_1 and B_2 on the information granularity level, and shifting of L_{opt} to the left in case of introducing novel measuring equipment and/or software package

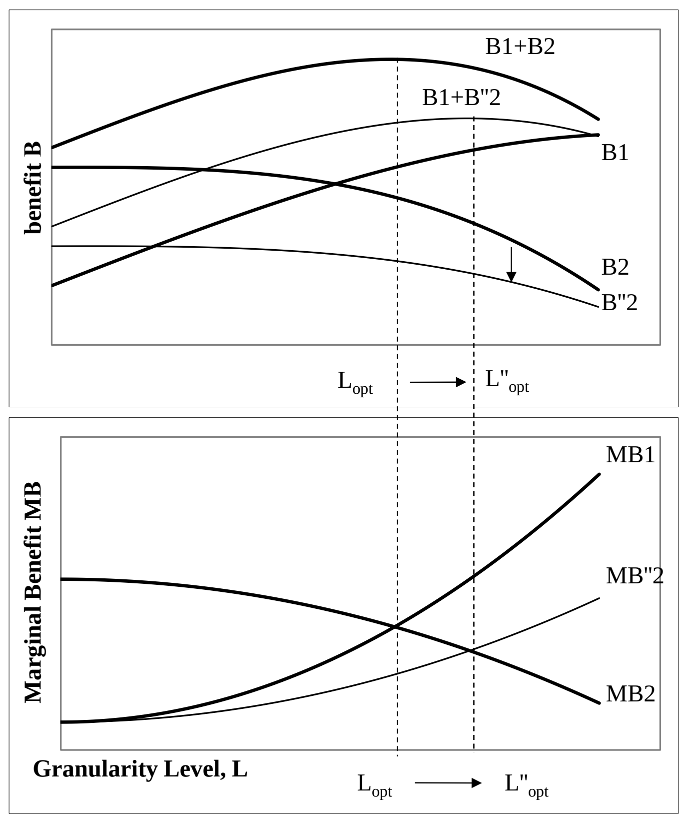

Fig. 4b. Dependence of partial benefits B_1 and B_2 on the information granularity level, and shifting of L_{opt} to the right in the same case because of knowledge acquisition cost increase, mostly in the region of lower L-values.

consequently, L_{opt} will move to the right at L''_{opt}, where $L''_{opt}>L_{opt}$, as shown in Fig. 4b.

Since the vectors ($L'_{opt}-L_{opt}$) and ($L''_{opt}-L_{opt}$) have opposite direction, the final placement of L_{opt} (i.e., to the left or right of its original value) value will depend on the form of the partial benefit functions and their parameter values. A Similar dependence is valid for the final placement of B_{max}, since its value is higher in the first and lower in the second case, respectively.

The process of transforming implicit to explicit knowledge, according to the Externalization (E) stage of the modified Nonaka's Model, can be improved if Internalization (I, within the same model) takes place by means of a semi-structured paradigm with proper flexibility/adaptability to be adopted by the individual subject. The information granularity level of this paradigm should be also in accordance with the intended purpose of structuring the corresponding KB and the mental infrastructure already existing in the researcher's mind, which might be simulated to an IA. Such a paradigm is conceptual clustering developed for unsupervised classification during the last two decades of the last century. Several algorithms have been designed/implemented, like COBWEB [11], GALOIS [12], ITERATE [13], LABYRINTH [14], SUBDUE [15]. According to the first of them, we design a description language (DL), for disambiguation, serving as a Controlled Vocabulary in terms of Ontologies, with probabilistic or possibilistic options by using probability density functions or fuzzy sets, respectively. The dendritic structure of data includes nodes representing respective *concepts*, while each concept represents a multiset of *objects*; in its turn, each object consists of a binary-valued property array; consequently, the data assigned to each concept are the corresponding integer property counts for the objects included in the respective node. Therefore, the taxonomy likelihood is the conditional probability of each property in the concept/node.

Subsequently, we implement this conceptual clustering algorithm in the case of 'low cost adsorbents' forming the root concept C(0) with 18 objects. The relative subordinate or 'child' nodes C(0, 1) and C(0, 2) stand for inorganic and organic adsorbents, while the latter is the 'parent' node of C(0, 2, 1), C(0, 2, 2), C(0, 2, 3), standing for agricultural residues, industrial wastes, activated sludge, respectively; the taxonomy properties (i, j, k) are *is a* dye adsorbent, *is an* oil adsorbent, *is a* heavy metal adsorbent (where, *is a*, corresponding also to *belongs to*, is the logical operator), taking the [1 OR 0]-value if the property exists or not, respectively, in each object, representing the referenced document where this information (about the property existence) is extracted from.

The respective knowledge representation scheme is shown in Fig [5], where boxes list actual objects and rhombi list attribute / property counts, according to the COBWEB algorithmic procedure described above. What is stored at or assigned to each concept node is the property count for (i, j, k) from which the corresponding likelihood P[x | C(…)] is calculated.

As the attributes take the discrete values 'zero' or 'one', the assignment of such a value is rather subjective, since it depends on experts' opinion about the minimum quantity adsorbed by a certain material so that this material can be characterized as successful 'adsorbent' and take the value 'one'. Although this quantity can be measured, other properties should be also evaluated either directly or indirectly measured (e.g. kinetic or thermodynamic parameters, respectively); even when all parameters are measurable directly, the weights with which each property contributes to the final result depends (to a certain degree) on the experts' opinion about the sub-optimal combinations that characterize a material as 'adsorbent'. Consequently, the assignment of fuzzy numbers within a Likert scale decreases only a certain part of such subjectivity while transferring another part from measurement to method evaluation; this means that the metamorphosis of implicit to explicit knowledge can only partially be achieved.

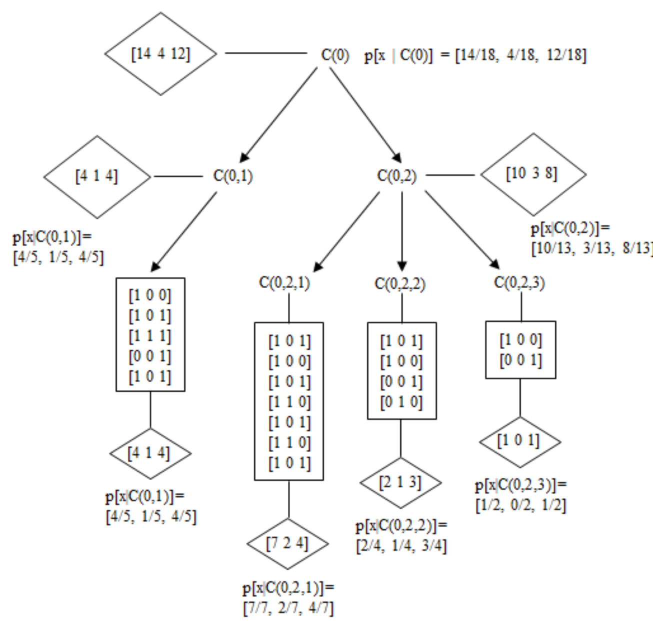

Fig. 5. Hierarchical partition of the concept C(0) 'Low-cost adsorbents', according to the 'conceptual clustering' algorithm COBWEB, as an aid for transforming implicit to explicit knowledge.

V CONCLUSIONS

The methodology we have designed/developed, under the form of an algorithmic procedure with 26 activity stages and 8 decision nodes, has been successfully implemented for transforming implicit to explicit knowledge in the case of novel lignocellulosic adsorbent production/application. More specifically, the following sub-procedures have facilitated this transformation within a techno-economic optimization framework:

1. Knowledge acquisition about the attitude of farmers/stakeholders (including tenants and owners/lenders of agricultural land) and occasional workers (including emigrant laborers) as regards their willingness to participate in waste lignocellulosic biomass collection with and without an economic

motive; the chi-squared test used as a statistical technique within the context of Contingency Valuation Method (CVM) of Experimental Economics gave unambiguous numerical results at 0.05 significance level indicating that economic support is indispensable on a permanent basis.

2. Estimation of optimal economic support by using a novel non-monotonic function to determine the expected benefits in both, materials/energy saving/substitution and environmental risk reduction, within an Industrial Ecology framework; this function includes implicit as well as explicit parameters, and their interaction facilitates performing the stages of externalization in the Nonaka's modified model. The numerical results obtained are within the limits set by the EU directives and the legislation of most member countries (i.e., up to 40% of the capital initially invested).
3. Parameter identification when more than one functions are used with the same dependent variable (the explanandum) and different set of parameters, serving also as independent/explanatory variables (the explanans); the implementation, referring to usage of the novel adsorbent under development in a fixed bed column, simulating an environmental protection process at industrial scale, exemplified thoroughly the situation.
4. Optimization of information granularity level when interlaboratory testing is performed to maximize techno-economic benefits by means of a trade-off between uncertainty decrease and cost increase (representing implicit and explicit knowledge, respectively); this sub-procedure is also heavily based on the transformation of implicit to explicit knowledge by the material quality examiners in laboratories performing repeatability and reproducibility tests as proved in the case of implementing conceptual clustering for 'low cost adsorbents' by means of the COBWEB algorithm.

APPENDIX

The cost functions taken into account in order to determine B_2 explicitly (opposing to implicitly defined B_1, as shown in Figs. 4a and 4b) are non-linear as regards L, since primary information is usually given under a linear form for sake of simplicity, convenience, comparability, and cost-saving in acquisition/storing/maintaining/retrieving/processing. On the other hand, the knowledge produced in stage C (of the modified Nonaka's model) and used as input for the determination of B_2 is based on 'Combination' of information, resulting to complexity/non-linearity. For example, in SEM (Scanning Electron Microscopy) images analysis for clustering of special characteristics of the biomass based adsorbent specimens (see Fig. 6), L is represented by magnification, which is given as a simple linear function of length; but clustering needs a surface rather than a line (array or row) and frequently heights or depths (up to a certain point) of the characteristic under examination should be taken into consideration, giving rise to the necessity to obtain/examine a 3D-image based on the standard deviation of pixel brightness [16], [17]. Consequently, the corresponding cost function of L becomes polynomial of second degree at least.

As regards the interlaboratory comparison of basic spectra, analyzing substances that are not necessarily pure there are at least three parameters which can be used; peak shifting, area displacement, shape distortion. Although this comparison is rather objective (based on measurement), the implications on health and the environment are rather subjective, as depended on the mixture suggested by the operators. Further analysis can increase the information granularity level L but with disproportionally higher cost. In practice, L_{opt} is approximated as the equilibrium point in a tradeoff between uncertainty and cost as shown in Figs. 4a and 4b.

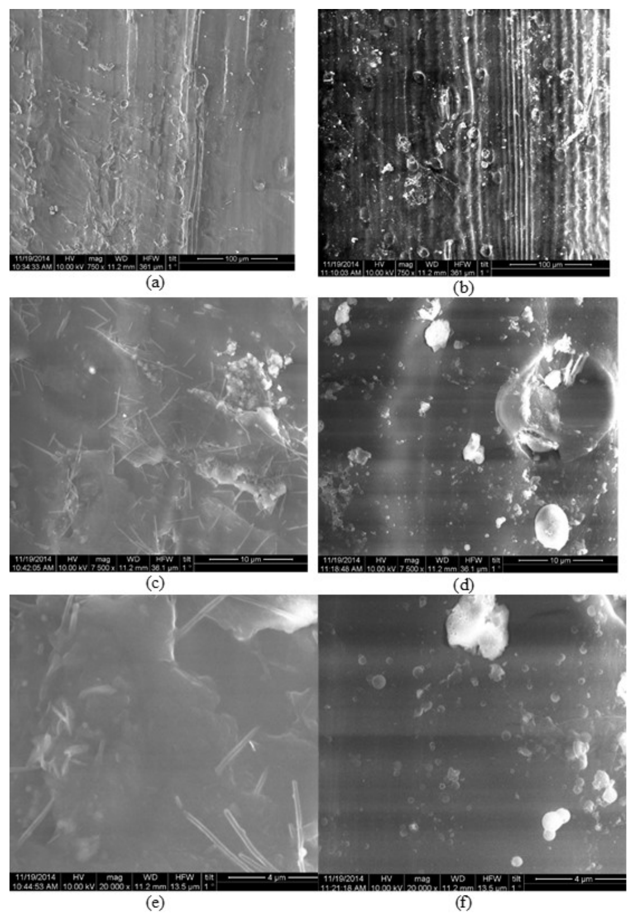

Fig. 6. SEM images of the untreated (a, c, e) and pretreated (b, d, f) product. The information granularity level L is represented by the magnifications, which are X750, X7,500, X20,000, for each pair; the corresponding cost is a non-linear function of L (see Discussion).

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