The discovery of operable knowledge features

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Abstract

Knowledge as the basis of science has up to now only verbally defined features which are not accepted between all sciences. On the other hand knowledge must have some interoperable, physical related features since otherwise we wouldn't be able to exchange knowledge between humans. With the discovery of operable features knowledge becomes, like information, a tool for interdisciplinary use.

Summary

Operable knowledge features are discovered which present a structure of knowledge which is independent of the specific meaning or use of knowledge. This discovery presents a completely new mathematically based concept of knowledge for different disciplines like economy, sociology, communication science, physics or biology. We explain how this arises by extending the well known Shannon concept of information. We show how competence and innovation are specific features of knowledge. Also it is explained how knowledge adds value to money. Some initial practical results of a pilot project in a company are discussed. Hints for application in different disciplines are given.

Extending the mathematical concept of information

Firstly we explain the fundamental concept of the measure of information and secondly we extend it for discovering operable knowledge features. Because this extension is based on mathematical methods it follows that operable knowledge features are independent of different meanings and uses of the word knowledge.

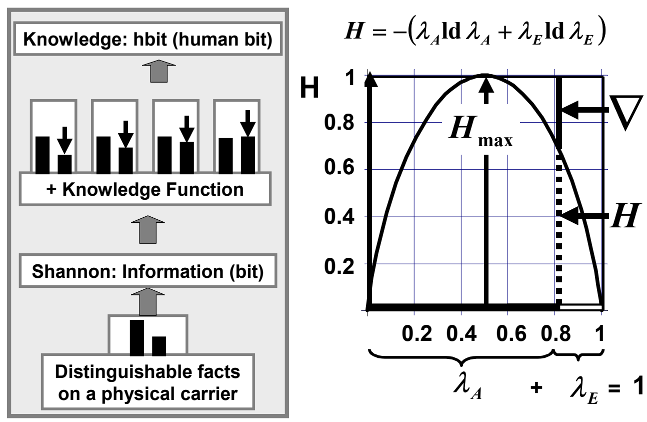


Figure 1: Information and knowledge

We start with Claude E. Shannon (Shannon, 1948) who discovered between 1945 and 1947 on the basis of the early work of Hartley a measure of information in the unit "bit". For determining an amount of information by that unit we count the appearances of facts (states) in the form of frequency diagrams and apply the Shannon formula on it. Thereby this "Shannon information" presents relations between distinguishable facts (states). That is symbolised in the lower left part of Figure 1.

In his article Shannon (1948) presented a famous curve (see right side Figure 1). He wrote: "*The entropy in the case of two possibilities p and q = 1- p, namely is plotted in Fig. 7 as a function of p.*"

$$H = -(p \log p + q \log q)$$

Formula 1: Shannon formula for Shannon's curve

This curve is mostly considered as the result of the complete possible spectrum of frequency diagrams which physically different coins may produce. It will be difficult to find in reality a complete set of such coins. So, for showing the real existence of that curve we manipulate coins in a way they present the needed frequency diagrams. That is symbolised by the arrows in the frequency distributions in Figure 1. There is shown the step by step adaptation to equal bars. That means we manipulate the world in relation to the outcome of a function. This ability of knowledge is substantial for the following analysis. Therefore we identify functions as the specific carriers of knowledge from which knowledge produces outcomes (like specific prepared coins). We define: knowledge generates facts in relation to functions. In this sense a coin is a fact that fits the requirement of a function set by knowledge. For showing the wide ranging implications of the definition we can put this briefly: a car is the result of a combination of energy and material following a specific input/output function (which is given by knowledge). We can also identify any assembling of different things in a group (flowers in a bouquet) as facts which are the outcomes of knowledge functions.

It is obvious that the frequency diagram of manipulated coins is not in accordance with the axioms of statistical methods (see for example van der Waerden, 1969). The probabilities p, q of the events are not independent, since we manipulate the coins the alternativity relation ($p + q = 1$) is given ex ante. In statistics it is one of the fundamental points that frequency diagrams are known only ex post, after we have measured (counted) the occurrence of the facts. Also the adding of the information values $p \log p$ and $q \log q$ in the Shannon formula needs in statistics the independency of the underlying events of the probabilities p, q. Since the famous Shannon curve produced by the help of knowledge is as real and identical to one related only to statistical axioms, we need a new mathematical concept which fulfils the requirements of both methods. Which also shows how alternativity ($p + q = 1$), coincidence $p \bullet q$ and at least the Shannon curve are in accordance with the setting of knowledge. If we have found this concept it presents some fundamental features of knowledge which we name operable knowledge features.

The fundamental idea here is to combine in a mathematical structure outcomes of physical reality with that of knowledge. So, we are looking for a structure of two numbers. Examples of such a structure are complex numbers.

$$
\begin{array}{ll}
1: & \underline{m} = m_A + i\, m_E \quad m_A, m_E \in \{+R\} \\
2: & m = m_A + m_E \;\; ; \;\; m \overset{!}{=} [\underline{m}] \\
3: & 1 = \lambda_A + \lambda_E \;\; ; \;\; \lambda_A = \dfrac{m_A}{m} \; ; \; \lambda_E = \dfrac{m_E}{m} \\
4: & \underline{\lambda} = \lambda_A + i\, \lambda_E \;\; ; \;\; \underline{m} = m\, \underline{\lambda} \\
5: & H = -\left(\lambda_A \,\mathrm{ld}\, \lambda_A + \lambda_E \,\mathrm{ld}\, \lambda_E \right) \;\; ; \;\; \lambda_E = 1 - \lambda_A \\
6: & H = -\left(p \,\mathrm{ld}\, p + q \,\mathrm{ld}\, q \right) \;\; ; \;\; q = 1 - p \\
7: & \underline{\lambda}^{\#} = \lambda_E + i\, \lambda_A = i \underline{\lambda}^{*} \;\; \Rightarrow \;\; \underline{\lambda}\, \underline{\lambda}^{\#} = i \underline{\lambda}\, \underline{\lambda}^{*} \\
8: & 1^2 = \left(\lambda_A + \lambda_E \right)^2 = \underline{\lambda}\, \underline{\lambda}^{*} + 2 \lambda_A \lambda_E \Leftrightarrow \lambda_A \lambda_E = \dfrac{1 - \underline{\lambda}\, \underline{\lambda}^{*}}{2} \\
9: & T = \dfrac{M}{H} \;\; ; \;\; \text{with } M = m
\end{array}
$$

Formula 2: Definition of complex alternatives

Firstly we define a specific type of complex numbers $\underline{m}$, named complex alternatives (indicated by an underscore, see line 1 of Formula 2) in which both parts m_A, m_E (which are always positive real numbers) are related to each other by the condition of line 2. The simple steps in line 3 and 8 lead to the Shannon formula in line 6 whereby the curve in Figure 1 is given. Line 3 shows that complex alternatives contain by themselves alternativity ($\lambda_A + \lambda_E = 1$) and simultaneously they contain the feature of coincidence: $\lambda_A \bullet \lambda_E$ (line 8). So, all the above mentioned conditions are fulfilled. Since there are infinite possibilities to choose different m_A, m_E for forming the sum $m = m_A + m_E$ there is an infinite set of complex alternatives which are defined by one single real number (the basic real number m). For example we can write (in relation to the symbol definition in line 2) for the real number m = 4 = [$\underline{4}$] = [2 + 2i] = [0.5 + 3.5i] = 4•[cos² φ + i sin² φ] = 4 [0.5 + 0.5i] etc. Since there is between a real number and its infinite set of complex alternatives a defined relation, these set (or subset) represents an outcome of the function [$\underline{4}$]. We name m_A the applicative number of $\underline{m}$ and define it as a result of a measure or count of distinguishable (physical) facts in general. We name the number m_E as the interpretative number of $\underline{m}$ which is set by knowledge. From lines 3, 4 we see that to each complex alternative is assigned a complex alternative norm $\underline{\lambda}$ from which we determine the Shannon information H in line 5. We can interpret any complex alternative as a frequency distribution of two bars of the high m_A, m_E. So any real m represents by its complex alternatives the infinite set of all such possible frequency diagrams.

After this formal introduction we demonstrate for a thrown coin that the use of complex alternatives is identical to the use of frequency diagrams. Let us assume we use a coin manipulated by knowledge. We decide to test the coin by 130 throws and have set thereby our basic real to m = 130. We know there exists the infinite set of [$\underline{130}$] complex alternatives, which represent the complete set of the possible outcomes of any test. So, knowledge is not presented in terms of a specific realisation but in terms of its complete function, given here by the uncountable set of complex alternatives. In this sense knowledge is a potential as it contains more possibilities than we can show in reality. That is necessary if knowledge shall be able to change the world in a way which is not determined by its given facts. We try now to find by measure that specific complex alternative which is related to the manipulated coin. Firstly we define what the "upper side" should be, that means we apply the number 1 to a real distinguishable appearance of reality (the one side of a coin). After a first throw the coin may present its "upper" side. We write therefore the complex alternative (1 + 0i), whereby m_A = 1 is the applicative number, which indicates the appearance of the "upper side". The second throw shows not the "upper side", consequently we interpret that the "upper side" appears in its alternative state and write (0 + 1i). After 130 throws we add the 130 found complex alternatives and may get (50 + 80i) which indicates we have found the "upper side" in 50 cases. The result we can write also in the form 130• (5/13 + 8/13 i) (see line 4). If we apply the Shannon formula (row 4 of Formula 2) on the alternative norm (5/13 + 8/13 i) we get exactly a point on the Shannon curve (Figure 1), for example: H = -(5/13·ld 5/13 + 8/13·ld 8/13). So, as this result is identical to a parallel measured frequency diagram, which has been established without use of complex alternatives, there is no conflict between usual statistical methods and complex alternatives.

If we get an alternative norm of (1/2 + 1/2i) knowledge has found a real distinguishable appearance which occurs to an other appearance alternatively. We speak of an identity, since both appearances occur identical like the both sides of an ideal coin appear. The Shannon formula presents for this case its maximum: $H_{max} = 1$. It is of importance that this identity – and we suppose identity in general - is not an effect of physical nature since it is impossible to find an ideal coin or an apparatus which presents it. Identity is a specific state of a knowledge function, is a feature knowledge can deal with. For example for the test of our coin we have used identity in our first step for identifying an "upper side".

In the following example we show how complex alternatives extend the frame of usual statistical methods. We construct a "black scale" with an ascending order of 100 points for indicating different appearances of black. Therefore we divide each part of our scale into 100 small squares which can be alternatively white or black. The possible combinations of m_A black and m_E white squares cover 100 different appearances of black. Standing before a large black wall we identify in 80 cases that the blackness of the wall is larger than that of the scale, so we get (80 + 20i) = 100•(4/5 + 1/5i) (the basis real is here m = 100). By applying the Shannon formula on the alternative norm (4/5 + 1/5i) we get again a point on the Shannon curve. The identity (1/2 + 1/2i) indicates here a form of grey. So the identity of black is not black by itself it is grey since grey presents at its one alternativity black and as its other white. In this sense each scale is a set of complex alternatives and therefore a function of knowledge. By this example we see that we have to free ourselves from seeing in the Shannon curve only a representation of statistics.

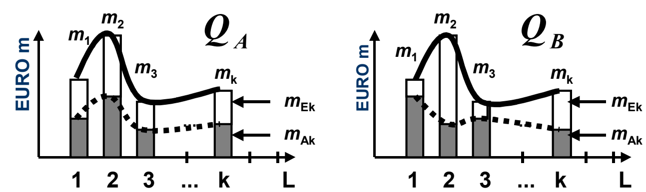
With this background we can interpret the Shannon curve (right side Figure 1) as the "informative outcome" of complex alternatives. We name the result of applying the Shannon formula on a complex alternative the human potential H and measure it in the unit hbit (human bit). For $\lambda_A = \lambda_E$ we get H = 1, which is the maximum of the human potential and which indicates a found identity. The difference ∇ (Nabla) between this maximum and its actual value H is: $\nabla = H_{max} - H$. It indicates the "difference to identity" and shows how much we have to change the world (to "innovate") for getting a new identity. Therefore ∇ is also named innovation impulse (see below).

Entropy and knowledge

It is shown how the second law of thermodynamics, the fundamental law of the increase of entropy S is influenced by knowledge.

We use the expression in Formula 2, line 8: T = M / H (with M = m). M is the number of repeated measures (counts). Since each measure needs energy, M determines the needed energy: E(M). We can interpret T as energy per alternativity (or identity): T = E(M) / H. For example knowledge is able to manipulate the natural flow of water in a way that it turns the wheel of a water mill. Therefore knowledge identifies an identity between the down movement of free running water and its alternative down movement at the one side of a wheel. The smaller this identity is the more water is not used alternatively, the smaller is H the larger is the innovation impulse ∇, the more we can change the world (innovate) for fulfilling that identity. We get the minimal T if knowledge has found an identity (H_{max} = 1), therefore we get the numeral result T = E(M). That means this form of temperature increases with the repeating of produced identities (e. g. repeating of measures as well as repeating of the turns of the water mill). In our example the water mill slows down the speed of the water stronger than it happens without the water mill. If S_P is the observable increase of the physical entropy and S_K that increase of entropy caused by knowledge, we can write: $S_K > S_P$. We can summarise: knowledge changes the world in a way that it accelerates the natural increase of entropy. This has been known to physics also up to now. The novelty is that we can formalize this and can derive that the largest effect is given if knowledge identifies identities.

Knowledge functions and Q-Distributions



1: $H(Q_B) \le H(Q_A) = H_{max}$; $\nabla = H_{max} - H = H(Q_A) - H(Q_B)$

2: $$H = -\sum_{k=1}^{L} \left(\lambda_{Ak} \,\mathrm{ld}\, \lambda_{Ak} + \lambda_{Ek} \,\mathrm{ld}\, \lambda_{Ek}\right) \text{ hbit} ; \ \lambda_{Ak} = \frac{m_{Ak}}{M} ; \ \lambda_{Ak} = \frac{m_{Ak}}{M}$$

3: $$H_{max} = H_S + 1 \qquad M = \sum_{k=1}^{L} \left(m_{Ak} + m_{Ek}\right)$$

4: $$T = \frac{M}{H} ; \ T_{min} = \frac{M}{H_S + 1} \le \frac{M}{H_{max} - \nabla} \le \frac{M}{H_S} \quad \frac{€}{\text{hbit}}$$

Figure 2: Economic human potential H

We can compose k-dimensional vectors of k complex alternatives $\underline{m}_k$, which will present operable knowledge features. If we use human skills and abilities as its components and money values for the m_{Ak}, m_{Ek} and if we present these vectors in a 2-dimensional structure as shown in Figure 2, symbolised by Q_A, Q_B we name it a Q-Distribution. Q-Distributions are specific economic knowledge functions. In (Kreft, 2003) is explained in detail how such Q-Distributions are established in companies. We give the name 'constituents' to the elements on the x-axis (the vector base). So, by using the Shannon curve in Figure 1 we have analysed a Q-Distribution with one constituent and we find all the derived results also on larger Q-Distributions. That is shown for the relation between H, ∇ in the line 1,2 of the formula in Figure 2. Line 2 shows the extended Shannon formula for Q-Distributions, which is a sum of the elements of line 4 of Formula 2. The result H represents the human potential of a person who possesses the skills and abilities presented in its Q-Distribution. Line 3 of Figure 2 shows that the maximal human potential H_{max} is one unit larger than the numerical value of its usual Shannon information: $H_{max} = H_S + 1$. H_S is the pure Shannon information which follows from the outer appearance of a Q-Distribution comparable to an identical frequency distribution.. That means only its outer structure is of importance. We get H_{max} for identical applicative and interpretative contributions ($\lambda_{Ak} = \lambda_{Ek}$, see Q_A). If the outer appearance is more even H_S becomes larger and otherwise it decreases. So each human potential contains by its Shannon information H_S a part which is related to its outer appearance. This is in accordance with the hierarchical relation between information and knowledge shown by Figure 1. In contrast the innovation impulse $\nabla = H_{max} - H$ reflects the inner situation of Q-Distributions. ∇ is the higher the more the inner structure of the Q-Distribution is different to its outer appearance (see dotted lines in Q_A, Q_B). So, in Q_B the innovation impulse ∇ is larger than in Q_A. ∇ is like a distance to identity. ∇ is in any case in the range: $0 \leq \nabla \leq 1$. If its value is nearer to 1 we are near to identity. T is proportional to M (see line 4, Figure 2) in which are summed up all the money values m of the Q-Distribution. The unit of T is money per human bit. The larger that T is, the more that one human bit is worth. Since H depends also on the inner structure of a Q-Distribution, it follows that T increases with the innovation impulse ∇.

Relations between knowledge and money

In the following we use in Figure 3 a TH-Diagram for applying physical concepts of thermodynamics to complex alternatives. We derive for the first time how money depends on knowledge features.

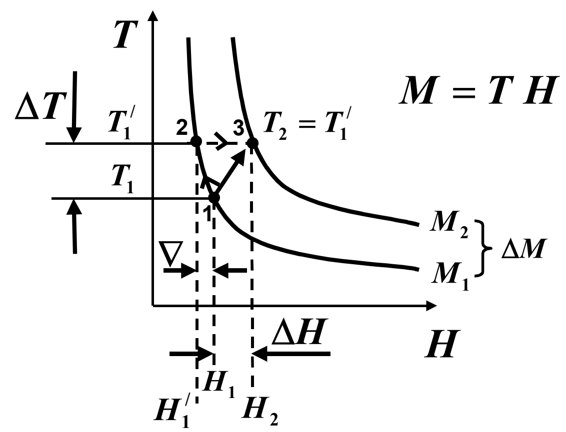


Figure 3: TH-Diagram for value added money

Each hyperbola branch of Figure 3 shows all the possible combinations of the T, H values of a Q-Distributions with fixed M. The "move" from the M_1–curve to the M_2–curve is mathematically executed in Formula 3. There we start in line 1 with the condition at point 1 of Figure 3, pass point 2 and reach by line 6 at point 3 of Figure 3. The important result in line 6 is that the formula presents on its left side the money added value ΔM / M and at the right side only knowledge features. Thereby we have determined for the first time how money values depend on knowledge. Because the innovation impulse ∇ appears positive in the counter of the ratio and negative in the nominator it dominates the outcome of ΔM / M. Above we have shown that the innovation impulse ∇ is "like a distance to identity". From Figure 3 we see that ∇ shifts the H_1 – value to the left, that means the temperature increases and we lose identities $\lambda_{Ak} = \lambda_{Ek}$. The move between point 1 and point 2 follows from the change of the inner appearance of a Q-Distribution, that is visualised by a change from Q_A to that of Q_B (see Figure 2). The step from point 2 to point 3 is done on a constant temperature level T_2, whereby we come to a new money value M + ΔM on which identity is again reached, since we have H_2 always counted in a non reduced form. Our move means, we have observed a non-identity on a lower level and found on a higher evaluated level identity again. Related to our above example of the water mill we know how to reduce loss of water which doesn't drive the wheel and thereby we get more energy and reach a new identity on the higher energy level. The value ΔH indicates in the formula an increase in human potential which enlarges in all circumstances the money added value. The more we learn the larger is the possible effect. The only term which reduces the left side is the total amount of human potential H in the nominator of the formula. The higher H the more constituents are in a Q-Distribution the more complicate it is to find a new identity between all that constituents again on a higher level of H + ΔH. If we start on a low levelled human potential H it is simpler to create additional values. This is what we can observe in modern economies. The higher the knowledge level (the higher H) the more complicated it is to find a specific effect (identities) which produces money added values.

$$\mathbf{1:}\quad \Delta M = M_2 - M_1 = T_2 H_2 - M_1 = T_1^{/} H_2 - M_1 \;\; ; \textbf{ with } \;\; T_2 = T_1^{/}$$

$$\mathbf{2:}\quad \Delta M = \frac{M_1}{H_1^{/}} H_2 - M_1 = \frac{M_1 H_2 - M_1 H_1^{/}}{H_1^{/}} \;\; ; \textbf{ with: } \nabla = H_1 - \mathbf{H}_1^{/}$$

$$\mathbf{3:}\quad \Delta M\, H_1^{/} = M_1 H_2 - M_1 H_1^{/} = M_1 (H_1 + \Delta H) - M_1 H_1^{/}$$

$$\mathbf{4:}\quad \Delta M (H_1 - \nabla) = M_1 (H_1 + \Delta H) - M_1 (H_1 + \nabla) \quad \textbf{with: } \nabla = H_1 - \mathbf{H}_1^{/}$$

$$\mathbf{5:}\quad \Delta M (H_S - \nabla) = M_1 (\nabla + \Delta H)$$

$$\mathbf{6:}\quad \frac{\Delta M}{M} = \frac{\nabla + \Delta H}{H - \nabla}$$

Formula 3: Money added values depending on operable knowledge

Competence and rationalisation potential in companies

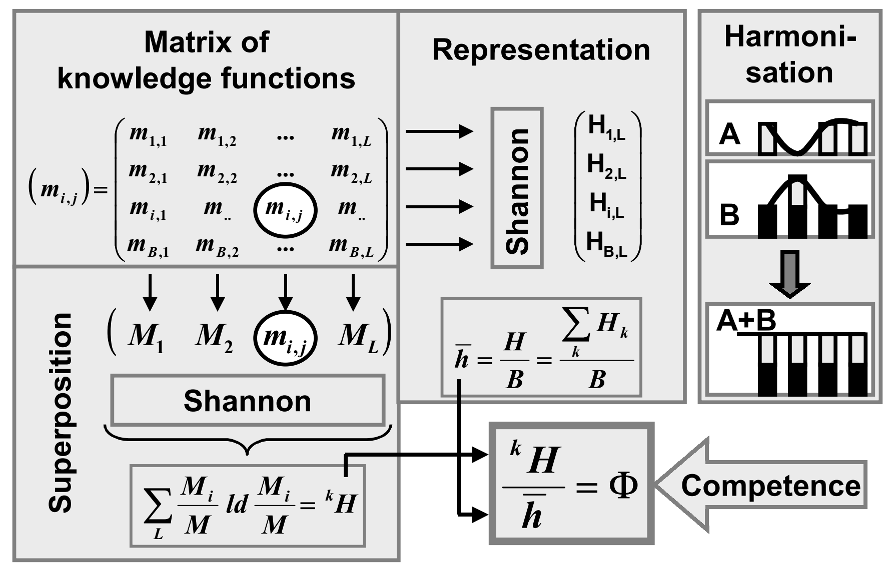


Figure 4: Competence as operable knowledge feature

We define economic competence as that set of skills and abilities which enable a company to compete successfully in the market. We show how competence follows from operable knowledge features.

In Figure 4 we assemble in the top left matrix different knowledge functions, for example all the Q-Distributions of the employees of a company or department. On this matrix we apply two mathematical methods which we name here "super positioning" and "average representation. In the right side part of Figure 4 is symbolised how the two Q-Distributions A, B are super positioned (which is simply adding their constituents). Super positioning indicates very strongly the appearance of a new constituent since the new function A + B has filled the gap of a constituent which is visible in the distribution A. The result of the application of the Shannon formula on a super positioned Q-Distribution is symbolised by ^kH. For the method of "average representation" we determine firstly the H-Values of each knowledge function in the matrix (that is, each row) and divide the sum by the number of rows and get the value h. In this case the contribution of the one encircled constituent $m_{i,j}$ is also divided and thereby decreased. We divide now ${}^{k}H$ by h and get the value Φ which is a measure of competency. This becomes intuitively understandable if we assume that in a first step we apply the method in the case where the encircled $m_{i,j}$ is not in the matrix. If in the second step the new constituent $m_{i,j}$ is also considered, this represents the case where, for example, one employee has learned a new skill. In this case the superposition immediately will register this, and the counter ${}^{k}H$ of the quotient increases, whereas the quotient Φ increases. This increase in Φ indicates a higher competence which is represented by the additional constituent. It should only be mentioned that a deeper analysis shows: the lower the competence the higher is the "rationalisation potential", since rationalisation potential indicates how often the same constituents are available. So operable knowledge features present a quantifiable limit for rationalisation beyond which a company cannot go if it wishes to retain its competence.

VALIDATION OF THE METHOD IN COMPANIES

Between September 2001 and February 2002 the Land Brandenburg (one of the 15 German counties) set up a first pilot project for the measurement of operable knowledge features in a company with 220 employees (System Data AG, Potsdam). The methods were applied over a period (1995 – 2002) for which all the company's control data was known. The question was: Would the methods of operable knowledge show details which the management did not know at the time but which they were able to corroborate later? The test was completely positive and smaller tests (in banking service centres) have led to similar results.

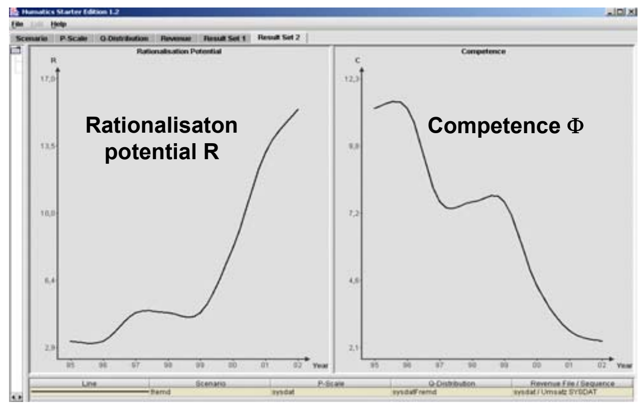


Figure 5: Screen shots System Data AG, Potsdam

One result was the determination of competence and rationalisation potential which are shown in the screen shot of Figure 5. The figure is the result of the practical test of the first version of the so called Humatics-Kernel-Software (HKS). All the mathematics as described above was performed by this software. The software enables us to determine such operable knowledge features as human potential H, competence Φ, innovation ∇ (Nabla), economic temperature T. The curves of Figure 5 show, for the period 1995 to 2002, the development of competence (right hand chart) and the development of rationalisation potential (left hand chart). First, the methods of operable knowledge which we have described were used to indicate a drastic decrease of competence. The management has confirmed this finding. During that period the company developed through a strong expansion phase, because there was strong market demand for the services of the company. The company reacted by taking on new employees which mostly had identical skills and abilities for fulfilling the market requirements. From our above analysis it is clear that this reduces the measure of competence and at the same time increases the rationalisation potential. The "saddle" in the right hand chart between 1997 and 1999 indicates a real stabilisation of competence in that period. The company during that time took on employees with new skills and abilities, which had mostly not been present in the company before that time. This “saddle” result was also confirmed by the management.

The results of this pilot have shown that for too long the company relied on its old knowledge base. They did not use their earlier good financial situation to train (or recruit) workers in order to develop a stable knowledge base. The company reacted after 2002 by large-scale dismissals of employees.

DISCUSSION AND CONCLUSION

An important aspect of the findings is that many features of operable knowledge describe also knowledge features in general. So, we can assume that operable knowledge informs us also about social development. We can interpret education as an alternative form of work. While education enlarges the knowledge base work has to look for innovation which means for findings of identities on higher levels. First social models based on the discovered methods show that unemployment is a direct result of the different evaluation of knowledge between the educational and the economic sectors of a society. In the economic sector knowledge appears as a high value to change the future but it is valued too low fro producing new knowledge in the educational sector.

The German Physical Society has formed a consortium of eighteen European universities, institutes, organisations and companies (e. g. Fiat, VW) and has suggested to the European Commission a large field test of operable knowledge features. We invite others to participate in this development.

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