nechansky

ENGINEERING EFFICIENCY

Knowledge Creation, Explicit Knowledge and Control

By

Helmut Nechansky

Nechansky, Helmut (2010), Knowledge Creation, Explicit Knowledge and Control, in Trappl, R. (Ed.), *Cybernetics and Systems 2010*, Proceedings of the 20th EMCSR, Austrian Society for Cybernetic Studies, Vienna, pp 342 - 347

Dr. Helmut Nechansky
Consultant on Systems Engineering

Rotenmuehlgasse 14 / 16
A - 1120 Vienna / Austria

Tel. + 43 / 1 / 817 5863
Email: hn@nechansky.co.at

Knowledge Creation, Explicit Knowledge and Control

By **Helmut Nechansky**
nechansky - ENGINEERING EFFICIENCY
Rotenmuehlgasse 14 / 16
A-1120 Vienna
Austria
hn@nechansky.co.at

Abstract

The paper analyzes primary and secondary knowledge creation (from practice to theories respectively from theories to certain products), as well as involved levels of knowledge (goals, social context, environment, technology, application, optimization, control and product). Forms of representing the knowledge on these different levels are discussed. It is shown that knowledge creation has to lead via all these levels towards explicit applicable knowledge represented as decision-rules of the form 'if {(actual data) (relation) (goal-value)}, then {trigger for a goal-orientated action}'. Only such decision-rules enable to control production processes.

1. Introduction

In this paper we want to briefly analyze the contents knowledge creation has to deal with.

We will first analyze primary aspects of knowledge creation that lead from practices to make certain products to the building of various theories. Based on that we will continue with secondary aspects of knowledge creation that start with already available theories to get from there to new applications and new products.

Then we will analyze what kinds of representation of knowledge are used during knowledge creation, and towards which representation this process has to lead. So we want to provide an overview on the hierarchical organization of knowledge and particularly the crispest applicable form of knowledge at the bottom of this hierarchy, which enables the immediate control of a production process. Finally we will discuss a few aspects of knowledge management derived from that.

2. Primary Knowledge Creation

Let us start with an analysis of *primary* knowledge creation, i.e. the top-down trial-and-error process to develop completely new knowledge. Here we want to focus on different levels of knowledge involved in that process (see table 1 for an overview):

(1) The development of knowledge starts with the specification of a *goal*, e.g. for a certain product or service. (Let us add in brackets as an illustrative example the age-old technology of casting a metal knife.)

(2) This goal is pursued in a certain *social context*, i.e. with and for certain persons (the manufacturers and the users of the knife).

(3) The goal is pursued furthermore in a certain *environment* (providing certain relevant local conditions, resources, etc.).

(4) A certain *technology* has to be developed to realize the goal (e.g. a certain furnace to melt the metal for the knife).

(5) The technology usually requires some equipment, which is specific for the *application* (e.g. using a certain die cast for a certain metal to cast the knife).

(6) Once technology and application-specific equipment work appropriate actions must be found to control the process and to always ensure a constant product quality (e.g. to fill the die cast always completely with metal).

The primary knowledge creation may end here, when the trial-an-error process led to an acceptable product (which depends on the initial goal-values!). Then it led to core knowledge comprising 7 different levels (goal, social context, environment, technology, application, control and product; See table 1, column 1).

Today usually two more steps are necessary:

(7) To improve an acceptable product and achieve higher quality goals (e.g. to make a harder, sharper, etc. knife) *optimization* has to narrow down the range of the application specific knowledge (level 5) to conditions necessary to realize the superior properties.

(8) Finally *optimal control* determines alarm values within the optimal range (level 6) and combines them with appropriate controller actions. So the process always stays in the optimal range and delivers a superior product.

	Goal-orientated Knowledge				Generalization	Theory
1	Goal 1a	Goal 1b	Goal 2	Goal 2	...	Market Research
2	Social Context 1	Social Context 1	Social Context 1	Social Context 2	...	Organization, Education, Law
3	Natural Environment 1	Natural Environment 1	Natural Environment 1	Natural Environment 2	...	Ecology, Environmental Law
4	Technology 1	Technology 1	Technology 1	Technology 2	...	Process- and Product Engineering
5	Application 1	Application 1	Application 2	Application 2	...	Physics, Chemistry, Material Science
6		Optimization 1b	Optimization 2a	Optimization 2b	...	Optimization Techniques
7	Control	Optimal Control 1b	Optimal Control 2a	Optimal Control 2b	...	Control Theory
8	Product 1a	Product 1b	Product 2	Product 2	...	Product Design

Table 1: Primary knowledge creation:
(1) From a goal to a product; (2) Different routes to other products; (3) Generalizations towards various theories.

Knowledge creation pursued to that point leads to knowledge *about optima*, which comprises eight different levels (goal, social context, environment, technology and application, optimization, optimal control and product; See table 1, column 2).

Based on that primary knowledge creation can continue in various forms. Let us name here just two examples:

Easiest way to expand the knowledge is to apply the technology to a new application, i.e. to develop another product (e.g. using another metal to make a knife, making metal vessels, etc.; See table 1, column 3).

Or it may be tried to make a known product with another technology (e.g. casting a metal knife in another type of furnace) at another place (see table 1, column 4).

In all such cases of knowledge creation derived from existing sources some aspects can be transferred directly, while on some levels new knowledge must be developed.

Those aspects of knowledge that can be transferred from one application to another can finally be generalized into various theories. This is the final and crowning achievement of primary knowledge creation. Some of these theories, which emerged and are relevant for production processes, are listed in table 1, right column.

So primary knowledge creation is a process that starts with the development of some goal-orientated, specific solutions and leads towards general theories. Primary knowledge creation is an ever ongoing process, but the better the theories it led to, the more it can be substituted by secondary knowledge creation, which can start with theoretical reasoning.

3. Secondary Knowledge Creation

Secondary knowledge creation can start, when theories of a sufficient range and accuracy are available:

Now developing a certain product or service can begin with deciding to use aspects of available theories, which are considered as relevant. Then these aspects are applied to achieve a certain goal and are eventually modified. Finally some goal-oriented, application specific concepts are derived thereof (see table 2).

We can here only mention that the decisive steps of secondary knowledge creation, i.e. the *decision processes* to select, apply, modify and derive concepts, usually does not get the attention it should get. For it is not the quality of the theories available, but the quality of the process to derive concepts from them, that determines effectiveness, efficiency and speed. Systems engineering [Patzak, 1982] is here the tool to make sure that conceptualization leads to a realistic result and so that only a few trial-and-error steps will be necessary to put a concept into practice.

But here we want to emphasize two other points:

(1) Obviously, whenever theories do not cover all the knowledge necessary for a new application, the trial-and-error of primary knowledge creation has to be applied.

(2) Even today theories allow only seldom to derive optimal concepts (level 6), while knowledge for optimal control (level 7) practically always has to be developed for every single product (see below).

So the quality of the secondary knowledge creation process depends on deriving concepts from theories. This can reduce developmental time and effort. But since usually no theories allow to deliver the crispest form of knowledge, i.e. controller models for optimal control, that remains a domain of primary knowledge creation.

Let us now analyze the forms, in which knowledge is represented at the various levels, and the differences between knowledge for optimal control and other forms of knowledge.

	Theory	Concep-tuali-zation	Goal-orientated Knowledge
1	Market Research	⇨	Goal Y
2	Social Sciences, Institutions, Law	⇨	Social Context Y
3	Ecology, Environmental Law	⇨	Natural Environment Y
4	Process- and Product Engineering	⇨	Technology Y
5	Physics, Chemistry, Material Science	⇨	Application Y
6	Optimization Techniques	⇨	Optimization Y
7	Control Theory	⇨	Optimal Control Y
8	Product Design	⇨	Product Y

Table 2: Secondary knowledge creation:
From theories via a goal-orientated selection and conceptualization process to a product

4. Representations of Knowledge

4.1. The Constraints for Realizing a Goal

The realization of a goal (level 1) for a product or service is constrained by the social context, the environment and the available technologies (levels 2 to 4).

Do determine these constraints one has to deal with knowledge represented in many forms, like texts, drawings, plans, flow sheets, diagrams, data, statistics and mathematical models. The precision of knowledge and the role of mathematics usually increase from level 2 to 4. But in all these cases the explicit relation between the goal and represented knowledge is usually far from obvious. Therefore the selection and conceptualization process of secondary knowledge creation, which we touched above, is so important.

4.2. From Goals via Theories to Applications

More crisp is the relation between goals (level 1) and the applications (level 5) once a technology (level 4) has been selected and the boundary conditions defined by the social context and the environment are clarified:

A product Y is usually defined by a list of properties y_i and the allowed ranges of a these properties:

$y_{1,min} < y_1 < y_{1,max}$,
$y_{2,min} < y_2 < y_{2,max}$,
...

Now theories may provide explicit equations like

$y_1 = f(a, b, c)$.

Equations allow to explicitly calculate process variables a, b, c, ... necessary to achieve the goal-value y_1. In that case an optimization may not be necessary (see below).

But often theories provide just approximate interrelations between process variables and properties of the form

$y_2 \approx f(a, d, e)$.

Then application specific knowledge has to be developed to clarify the exact relation between properties and variables. Such knowledge takes the form of ranges of process variables a, b, c, ... , that are necessary to keep the properties of the product y_i in their respective allowed ranges $y_{i,min} < y_i < y_{i,max}$:

$a_{min} < a < a_{max}$,
$b_{min} < b < b_{max}$,
...

This is often called a ‘process window’. It is the basic knowledge for any application.

4.3. From Applications to Control

The *cognitive knowledge* about limits like a_{min} and a_{max} is necessary, but obviously not sufficient, because it does not cover the decisive *know how* about appropriate *actions* to really keep the process variables within that range. Let us mention here that knowledge about actions is unfortunately not really a concern of knowledge management [Baskerville and Dulipovici, 2006].

To realize basic process control with a feedback system requires at least two decision-rules of the form:

if {(actual data a_t) > (a_{goal})},
then {trigger for a goal-orientated action (1) towards a_{goal}};

if {(actual data a_t) < (a_{goal})},
then {trigger for a goal-orientated action (2) towards a_{goal}}.

So to actually control the process the *theoretical model* determining the limits a_{min} and a_{max} has to be combined with at least one goal-value a_{goal} within that range and an *action model*. This action model represents the practical *know how* of goal-orientated actions, i.e. how, when, where, how strong, how long, etc. to intervene in the process to correct any deviations from the goal and to keep the process within the limits.

Feedback as exemplified above is necessary for process control, but not sufficient for most applications today. Today usually an optimization has to follow once the process window of an application was determined.

4.4. From Applications to Optimization

Elaborated theories available in the form of explicit equations may allow to narrow down a process window $a_{min} < a < a_{max}$ to an optimal range $a_{opt,min} < a_{goal} < a_{opt,max}$ that should lead to a superior result for a property y_i:

$a_{min} < a_{opt,min} < a_{goal} < a_{opt,max} < a_{max}$,
$b_{min} < b_{opt,min} < b_{goal} < b_{opt,max} < b_{max}$,
...

But in many cases sufficiently elaborated theories are not available, even today. Then an optimal range to realize a product of a constant high quality cannot be determined theoretically. In that case only practical investigations can clarify how the variation Δy_i of a property y_i of the product depends on variations of process variables Δa, Δb, Δc, ... Here optimization techniques (like design of experiments, etc.) [Petersen, 1991] are necessary to determine the actual interrelations of these variations:

$\Delta y_1 = f\ (\Delta a, \Delta b, \Delta c) + E_{I,1}$.

$\Delta y_2 = f\ (\Delta a, \Delta d, \Delta e)\ ) + E_{I,2}$.

...

Here $E_{I,i}$ is the residual error, i.e. is the remaining variation, that cannot be explained by this model.

Even if elaborated theories are available, it often turns out that not only the theoretically known process variables a, b, c, ... determine the variation of the properties y_i of the product. Let us mention that this fact goes widely unnoticed in works on knowledge management. Here optimization techniques [Petersen, 1991] have to identify the additional application-specific variables r, s, t, ..., which significantly contribute to that variation. Then optimization finally leads to equations of the form

$\Delta y_1 = f\ (\Delta a, \Delta b, \Delta c, \Delta r, \Delta s, ...) + E_{II,1}$.

$\Delta y_2 = f\ (\Delta a, \Delta d, \Delta e, \Delta r, \Delta t, ...) + E_{II,1}$.

...

$E_{II,i}$ (< $E_{I,i}$) is the residual error, i.e. the remaining variation that cannot be explained by the optimized model, but can be tolerated given the goals for the application.

It is this kind of statistical knowledge that is the *theoretical base* to control a process optimally.

4.5. From Optimization to Optimal Control

Given the knowledge about the interrelation between the variation of properties of the product and the variation of the process variables an appropriate optimal control regime can be elaborated. Here again the knowledge about the optimal range of variations has to be combined with an action model for optimal control. That has to make sure that any variation in the process variables Δa, Δb, Δc, ... Δr, Δs, Δt, ... is kept that low, so that the resulting variation Δy_i in properties of the product never leaves the allowed range $y_{i,min} < y_i < y_{i,max}$:

(1) Therefore alarm values a_{alarm} and indicators a_{ind} have to be determined within the optimal ranges of process variables $a_{opt,min} < a_{goal} < a_{opt,max}$, in the form

$a_{opt,min} < a_{alarm,min} < a_{ind,min} < a_{goal} < a_{ind,max} < a_{alarm,max} < a_{opt,max}$,
$b_{opt,min} < b_{alarm,min} < b_{ind,min} < b_{goal} < b_{ind,max} < b_{alarm,max} < b_{opt,max}$,
...

First alarm values are determined by calculating when the *variation* of process variables Δa, Δb, ... would cause the property y_i of the product to lie outside the allowed range $y_{i,min} < y_i < y_{i,max}$ [Dietrich and Schulze, 2009].

Then indicators are determined to show when the process starts to deviate form a secure middle range around the goal-values towards an alarm value.

(2) Based on that appropriate corrective actions have to be found for all these alarm values and indicators, so that the process variables can never leave the optimal range. Therefore the final knowledge to optimally dominate a process takes the form of *sets* of decision-rules, like

if {(actual data a_t) < (a_{goal})},
then {trigger for a goal-orientated action (1) towards a_{goal} };

if {(actual data a_t) ≥ ($a_{ind,max}$)},
then {trigger for a stronger goal-orientated action (2) towards a_{goal} }.

So optimal control requires sets of decision-rules relating to *every* relevant variation in the process variables Δa, Δb, Δc, ..., Δr, Δs, Δt, ..., a goal-orientated action.

So we need here a sophisticated *action model* defining all the technical and / or organizational measures (who, how, when, where, how strong, how long, etc. is to act) to keep the process variables always in the secure range between the indicators and with that the properties of the product in the allowed range. This action model consists of many single inconspicuous but decisive measures, like PID - controllers appropriately set to trigger the right action at the right point in time, alarms reaching the right persons, action plans elaborated and known to the persons in charge, all workers instructed, etc., etc. So unlike the theoretical model, the action model is a distributed model providing locally the know how to control the process.

Even today this practical *know how* about appropriate controlling actions is often underestimated in relation to theoretical knowledge. But actually if not for *every* relevant variation in the process a practical controlling action is found, a theory remains useless. (To illustrate that let us refer to today's car industry: The difference between the more or less successful carmakers does not lie in their theoretical knowledge. It lies in their action models, to control their processes and to keep them more or less within limits. The names of the companies having the superior know how to do that are well known.)

5. Explicit versus Tacit Knowledge

The differentiation between explicit and tacit knowledge [Polanyi, 1958] is often used in knowledge management:

Here explicit knowledge usually is understood as knowledge than can be expressed in words and numbers and can be shared with others in books and formulae, etc.

On the other hand tacit knowledge is defined as vague, believed, presupposed, normative and non-codifiable knowledge that depends on personal experience and is difficult to share.

Based on our short analysis of knowledge creation making explicit levels and representations of knowledge, we propose now a specification of what can only count as unequivocally explicit knowledge:

(1) We suggest that explicit knowledge has to contain terms of the form {(data) (relation) (data)} respectively {(data) (relation) (goal-value)}, where the (relation) determines an unequivocal relation of order between the two: This requires relations of the form <, ≤, =, ≥, >.

We suggest that other relations between data like <<, ≈, >>, require further explanation, and therefore can alone neither be unequivocally taught to others nor be directly applied by others for unequivocal actions (for examples see below).

Then explicit knowledge can only take the form of mathematical equations y = f (a, b, c), process limits (like $x < x_{max}$) and verbal descriptions of that form, like 'The concentration of X has to be below x_{max}'.

(2) To put such explicit knowledge in practice the terms of the form {(data) (relation) (goal-value)} have to be combined with specified actions with a known goal-orientated effect. This gives the final form of knowledge we found in our analysis of knowledge creation, i.e. decision-rules that enable control having the form

if {(actual data) (relation) (goal-value)},
then {trigger for a goal-orientated action}.

Only such explicit knowledge, using relations <, ≤, =, ≥, or >, enables goal-orientated behavior and control.

From that definition of explicit knowledge follows that all other forms and representations of knowledge are tacit knowledge. This comprises particularly:

(1) In the primary knowledge creation process all assumptions about the relevance of knowledge from higher levels 2 to 4 for a certain application, till they are confirmed in successful process control, i.e. are transformed in explicit knowledge as defined above.

(2) In the primary knowledge creation process all assumptions that knowledge can be transferred from one application to another, as well as that it can be generalized into a universal theory.

(3) In the secondary knowledge creation process all inverse assumptions about the relevance of knowledge, i.e. what theories can contribute to a certain application.

(4) Finally all forms of knowledge that express assumed, likely, fuzzy or rough interrelations, using relations of order like <<, ≈, >>, etc. or express such relations verbally.

Two examples have to suffice here to illustrate our differentiation between explicit and tacit knowledge:

Let us first take an example from environmental law (level 3): A law only provides explicit knowledge, if it makes an unequivocal statement like 'The concentration of X has to be below x_{max}'. Then obviously any concentration above x_{max} is a violation of the law. But if a law requires to apply 'the state-of-the-art' to keep the concentration of X 'low', then this requires interpretation and is tacit knowledge. That may finally require a decision by a judge to define exactly that 'low' is $x < x_{t,max}$ given the technologies at time t. This is point (1) of our requirements for explicit knowledge above. Only after that, point (2) can be applied, i.e. if the law requires a corrective action, because x is not 'low'.

Another example may be taken from 'expert' knowledge about an application (level 6): Such knowledge is often available in fuzzy terms, like 'Keep T a little below T_{max}'. This tacit knowledge can be made explicit by fuzzification, i.e. translating these terms in a range $T_{min} < T_{opt} < T_{max}$ and assigning an appropriate fuzzy function to that range. Of course, this is point (1) of our requirements for explicit knowledge above. Combined with appropriate actions to keep T in that range, this knowledge can be used for fuzzy control [Pedrycz, 1989]. This is point (2) of our requirements above to get to applicable explicit knowledge.

6. Explicit Applicable Knowledge Consists of Crisp Decision-rules

We could show here again that knowledge follows in principle the elementary decisions found in simple feedback systems [Nechansky, 2006]:

if {(actual data) (relation) (goal-value)},
then {trigger for a goal-orientated action}.

We showed elsewhere [Nechansky, 2009], but did not touch that here, that complex decisions follow the same principle, but use decision-rules that may contain any number of the terms {(data) (relation) (goal-value)}:

if {[(actual data 1) (relation 1) (goal-value 1)],
OPERATOR1
{[(actual data 2) (relation 2) (goal-value 2)],
OPERATOR2
...
then {trigger for a goal-orientated action}

The OPERATOR used here may be any logical operation AND, OR, NAND, NOR, XOR respectively NOT.

We added here that knowledge creation has to lead finally to crisp decision-rules using only relations of the form <, ≤, =, ≥, > (and not <<, ≈, >>, etc.). Only such crisp decision-rules give explicit, applicable knowledge.

From this analysis follows furthermore, that the sum total of the explicit and applicable knowledge is equivalent to the sum total of crisp decision-rules that are available to control a certain process.

7. Some Consequences for Knowledge Management

From this short analysis of knowledge creation a few consequences for knowledge management can be derived that go widely unnoticed in the field today [Baskerville and Dulipovici, 2006]:

1. Explicit applicable knowledge to control production processes requires crisp decision-rules.
2. Decision-rules consist of a 'theoretical', 'cognitive', 'knowing that' part, containing one ore more terms of the form {(actual data) (relation) (goal-value)}, which determine deviations from a goal.

   They presuppose the exact definition of goal-values (optimal -, mean -, min - max -, alarm values, etc., as discussed above). Knowledge management has to provide first these higher level goal-values needed to evaluate the data entering in lower level decisions.
3. And decision-rules contain a 'practical', 'action selecting', 'knowing how' part, relating a certain corrective, goal-orientated action to every cognitively determined deviation from a goal-value.

   So knowledge management has not only to provide the goal-values necessary to define the cognitive terms {(actual data) (relation) (goal-value)}. Even more importantly it has to provide an *action model* representing the practical *know how* of goal-orientated actions (i.e. who, how, when, where, how strong, how long, etc. is to act) to successfully control a process. We suggest that providing that know how locally, where deviations from a goal are recognized and can be corrected, is more effective and efficient, than to manage theoretical knowledge stored somewhere in a database.

We suggest that all other aspects of knowledge management - the tacit knowledge sought and acquired on all higher levels of the knowledge creation process - have to be selected and organized so that they can lead to crisp decision-rules, i.e. that explicit and applicable core knowledge, which actually enables control.

References

[Baskerville and Dulipovici, 2006] R. Baskerville and A. Dulipovici, The theoretical foundations of knowledge management, *Knowledge Management Research and Practice*, 2006, 4, 83 - 105,

[Dietrich and Schulze, 2009] E. Dietrich and A. Schulze, *Statistische Verfahren zur Maschinen- und Prozeß-qualifikation*, Hanser, Munich, 2009

[Nechansky, 2006] H. Nechansky, Special States in Goal-Orientated and Adaptive Systems: Base for Definition of Information, in Trappl R. (Ed.), *Cybernetics and Systems 2006*, Vienna, 2006, 97 - 102

[Nechansky, 2009] H. Nechansky, Elements of a Cybernetic Epistemology: Design Rules for Complex Goal-orientated Systems, *Systems Research and Behavioral Science*, 2009, 26, 411 - 427

[Patzak, 1982] G. Patzak, *Systemtechnik - Planung komplexer innovativer Systeme*, Springer, Berlin, 1982

[Pedrycz, 1989] W. Pedrycz, *Fuzzy Control and Fuzzy Systems*, Wiley, Chichester, 1989

[Petersen, 1991] H. Petersen, *Grundlagen der statistischen Versuchsplanung*, ecomed, Landsberg, 1991

[Polanyi, 1958] Polanyi, Michael, *Personal Knowledge*, University of Chicago Press, Chicago, 1958