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A MULTI-EXPERT ARCHITECTURE FOR CREDIT RISK ASSESSMENT

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RÉSUMÉ

Les travaux réalisés sur les systèmes experts, systèmes destinés à modéliser les processus cognitifs des êtres humains, ne se sont pas avérés aussi prometteurs que prévu. Dans ce cahier, nous analysons certaines des limites des systèmes basés sur les connaissances puis nous proposons une nouvelle approche à la modélisation des processus de décision. Elle intègre connaissances de surface et connaissances basées sur les modèles multi-attributs de traitement de l'information à travers une structure multi-agent pilotée par un méta-modèle. Cette approche s'appuie sur les recherches effectuées en psychologie cognitive et en théorie de la décision. Elle nous semble être une voie prometteuse dans le développement des systèmes experts de seconde génération. Le système a été appliqué avec succès à l'évaluation du risque crédit entreprise.

Mots-clés : Système multi-expert, méta-connaissance, méta-expert, stratégie de contrôle, modèles de jugement multiattributs, évaluation du risque crédit entreprise.

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ABSTRACT

Knowledge-based systems (KBS) are aimed at representing human expert cognitive processes in specific domains. This new methodology held promises but did not lead to expected results. The purpose of this paper is to address some of the limitations of the KBS. Then, a new approach to decision process representation is proposed. It integrates shallow knowledge and multiattribute decision-making models through a multi-expert structure driven by a meta-model. This approach builds on psychological research on information process and seems to be promising in developing second generation knowledge-based systems. The system has been successfully applied to corporate evaluation and risk assessment.

Keywords : Multi-expert system, meta-knowledge, meta-expert, control strategy, multi-attribute decision-making models, risk assessment, corporate evaluation.

1. Introduction

Decision-making problems in credit risk assessment and authorization are often too complex to be treated by conventional methods. They involve judgmental procedures which are by nature non-deterministic. Assessment involves making judgments based on uncertain data and it often leads to reasoning on several levels when the entity has a complex structure broken down into sub-domains, as is the case, for example, for a company. The process then leads to judgments for each of the sub-domains or component parts, and so to partial assessments. The final assessment usually emerges after having taken into account all the interdependencies among the various characteristics and components.

The problem is compounded when the non-deterministic nature of the assessment process is taken into account. In judging an entity (a company, for instance), the analyst gives a different weighting to each component. This can evolve dynamically as partial results appear. The relative importance of each produces an order of priorities as the assessment phases take place. The nature of the expertise brought to bear in the analysis strategy will vary with the nature of the problem and with the user, and methods used in addressing such problems must be explicitly stated. In all of this, meta-knowledge emerges, enabling the system dynamically to construct an appropriate model taking into account the specificity of each case being considered.

The CREDEX (Credit Expert) system presented in this article is an attempt to address these different problems. We have applied it to corporate assessment, or, more precisely, to the assessment of the risk involved in granting a loan. Its object is to help the analysists responsible for bank loans to judge the quality of a company seeking funds. A match is made between the level of risk and the loan request, together with an explanation of what is involved.

Although we have used credit analysis in this demonstration, our object has been to develop a system which represents the process of complex and structured entity assessment in a general fashion, whatever the field of application.

This article outlines the characteristics of the appraisal process and the systems already available in this area and their limitations, and shows the original aspects of the CREDEX system, providing an answer to certain of the problems highlighted. It will go on to describe the system itself, detailing its multi-phase operation, its architecture, its components and more particularly the structure of the meta-expert system

2 Notions on the domain of application.

In this paragraph, we shall present the characteristics of risk analysis, the existing tools, and their limitations. These have lead us to create a flexible, general architecture for the system, thus enabling it to adapt to any assessment process, and to design and structure its knowledge base.

2.1 Risk analysis.

Judging a company and assessing the risk for a loan is a complex and costly task, for loan application files take several days to complete. The outcome often depends on the analyst's experience, his perspicacity and overall impression of the loan applicant firm, his view of the industry sector in which the firm operates and his knowledge of the bank's lending policy.

On further analysis, we highlighted the criteria used by the experts, as well as the four main components of risk [Chevalier, 82]: commercial, financial, managerial and industrial risk.

Commercial risk covers product-market risk, customer risk, and the risk derived from the company's activity. The product-market risk is assessed for each product by taking into account the rate of market evolution, of the product's contribution to margin, and in certain cases life-cycle. A company's weakness is often the result of customer risk. Data is provided by detailing of late payments, of the type of customers, and of bad debts rates. *Financial risk* has several aspects: financial structure, profitability, debt, and cashflow. The human factor counts for a high proportion of corporate risk: *managerial risk* studies the managerial team, the composition fo shareholders capital, succession problems where necessary (successoral risk) and decisional risk as a function of the decision making process and company organization. Finally, *industrial risk* concerns the nature and amount of investment and the quality of research. Naturally, this risk analysis depends on the importance of each element, for example the weight of each product in the total net sales, or that of each type of customers within the total clientele.

2.2 Existing tools

There are three main categories of tools to help the analysist to assess corporate risk: tools based on multivariate statistical methods, interactive decision support tools , and tools based on artificial intelligence.

Statistical tools provide algorithms with which to rank companies in levels of risk , and/or to calculate a score representing the degree of risk (e.g. discriminant analysis, multiple regression, cluster analysis), using financial ratios considered as significant. The commonest methods are those of "credit scoring", which establish a discriminant function using certain of the company's fincancial ratios, and rank them in high-risk or low-risk groups [Altman 83]. The Banque de France's "Fonction Z" is based on the same principle.

Interactive decision support systems (D.D.S): These systems integrate databases, optimization models, statistical methods and spreadsheets. The system and the analyst interact by means of a question-answer type language (fourth generation language) or graphic language. These systems are used to create ratio analysis statements or other financial syntheses for sensitivity analysis and for simulations of different financial policies [Sprague 82], [Bonczek 81].

Tools based on artificial intelligence: originally designed in relatively structured areas where behavioral variables do not occur, expert systems have begun to interest the business sector in recent years [Reitman 84], [Lampert 85], [Benchimol 87], [Ernst 88], particularly the financial and banking sector [Johnson 84]. It must however be noted [Johnson 84] that less than 10% of the systems surveyed in the United States are in management. The limited development of expert systems in management is mainly due to the eminently suggestive nature of management expertise, and also to the difficulty in coming to an agreement on the heuristics which lead to a "good" judgment or a "good" decision.

The integration of Decision Support Systems and expert systems resulted in systems called "Expert Support Systems" [Blanning 84], [Bosman 85], [Holsapple 85], [Luconi 86]. Some of the most well-known published systems in the field of company assessment and business loan evaluation are FINEX [Kerschberg 85], SAFIR [Rechenman 87], FSA [Mui 87], FANFARE and its predecessor FAULT [Silverman 87], MARBLE [Shaw 88], CLASS [Duchessi 88], COSIE [Pham Hi 88], which make a financial diagnosis of the company by means of ratios, MATIAS [Kontio 88], assessing loans to farmers, PREFACE-EXPERT [Sénicourt 87], analyzing corporate creation projects, SYNTEL [Reboh 86], [Duda 87] combining risk assessment of various factors entered by the user to give an overall financial risk. FSA is able to take into account information contained in the footnotes of financial statements.in order to analyze corporate financial reports. Private systems developed by banks and consultants, of which we have insufficient knowledge, such as Personal Financial Advisor (Arthur D. Little), Lending Advisor (Syntelligence), PlanPower (APEX), Morgage Loan Analyser (Arthur Andersen), Corporate Financial Advisor (Athena Group), should also be mentioned.

These systems may be divided into two categories: products using zero plus inference engines running on micro-computers, and much more sophisticated products often based on ART and KEE, used on workstations.

2.3 Limitations of existing systems

The main advantage with all intelligent D.S.S lies in their highly developed interfaces, such as graphic, windowing, and almost-natural language. This makes them very user-friendly. However, they do have some limitations:

— Risk analysis is incomplete: most systems only analyze the risk from its financial aspect and do not take into account the commercial, managerial and production aspects of the company. This approach is very restrictive and it is difficult to detect the causes of problems with a view to taking possible corrective measures.

— Even if they do measure risk to some degree, these systems do not take into account the non-deterministic nature of the assessment.

— The architecture is that of first generation systems: first, their reasoning is superficial, using relatively short inference chains to reach a conclusion, and second, they only use one type of knowledge: relational knowledge or surface knowledge; both of which are a precompilation of more complex knowledge [Buchanan, 1984]. In this type of architecture, the characteristics of the problem are linked to possible solutions via diagnosis rules [Chandrasekaran 84]. By definition, they are dependent on the field and the expert, and it is difficult to use them to construct similar systems.

— The representation of knowledge is rigid: some systems have not found a suitable solution for the problem of combinatory explosion in the search space. They are based on a set of rules in a codified tree-pattern (or a decision table, which is the same thing) of all the possible cases. They are designed for the study of all combinations of the indicators and their modalities [Ben-David 86]. In the case of n indicators, each having m modalities, the system must examine mn combinations. The time needed for this is too great when n is large, as for example in the assessment of a company: if n = 10, m = 3 ("satisfactory", "average", "poor") - m = 310 = 59049. The designers of such systems will either have to eliminate certain infrequent combinations (but if they do occur, then the system will not be able to draw a conclusion), or to artificially structure the knowledge in a hierarchical manner.

3 General Characteristics of CREDEX

In order to provide an answer to the preceding problems, and taking into account the specific aspects of the domain, we have designed the CREDEX system. It operates by using economic, financial and social data on the company and its sector of activity, and also on the bank's lending policy. It provides:

— a diagnosis of each of the firm's functions in terms of weaknesses and strengths,
— the degree of partial risk inherent in each function;
— the degree of overall risk associated with the granting of the loan, and
— suggestions regarding loan acceptance.

CREDEX works as an "intelligent" support for corporate assessment. It guides the user collecting information and only asks the questions corresponding to the situation being examined. To avoid overlong dialogue, the system first asks for a minimum of information (name, type, sector of the firm), and then asks further questions if the data sought is a necessary component of its reasoning. For example, a description of future managers' competence is only asked for if a successoral problem is examined.

CREDEX is original because:

1) its multi-expert structure is driven by a meta-model. This structure is based on the research carried out in cognitive psychology and decision theory [Nisbet 80], [Einhorn 81], and [Brehmer 86]. This research first of all suggests that any assessment process is one of phases, in which the initial phase of assessing sub-domains is followed by a phase of choosing the appropriate judgment strategy, and then by a judgmental phase in which a combination of multi-attribute aggregation rules is applied. It goes on to suggest that analysts, like everyone, seem to rely upon rules for processing and aggregating information which differ from those of the probalistic approach.
2) its processes qualitative information. At each level of the reasoning, conclusions are assessed on interval scales, e.g. a five-point scale for risk (from "very high" to

"very low"). This method of reasoning avoids incoherency in assessing degrees of risk such as they might appear in a quantitative, probabilistic approach.

3) it integrates both surface and deep knowledge of the domain. The former consists of simple heuristics which enable experts to accept or reject a loan application. The latter is a deeper understanding of the information aggregation process, and determines how far a loan is risky.

4) it uses multi-attribute models to aggregate elementary judgments.

Each of these points will be dealt with in detail below.

4 Assessment phases and ponderation system

The different judgments of the firm's characteristics are measured on a five-point interval scale (from "very positive" to "very negative"). As mentioned earlier, analysts are not capable to give numerical assessments of risk similar to certainty factors, or the other coefficients suggested by the literature [Buchanan 84]. In CREDEX, the level of risk associated with each loan application is determined through a multi-phase process, using the factual and associative knowledge of the domain [Pinson 89], viz:

— A weight g_j, on a 7-point interval scale from "very-important" to "not-really-important", is associated with each function or sub-domain j of the company. These ponderations measure the weight of the function as seen within the global risk assessment. Either the user gives the g_js interactively, or the meta-expert infers them as being a function of banking policy B, the sector of activity S, and of the assessment goal O:

$$g_j = f(B, S, O)$$

For example, if a company is assessed for a loan, the commercial function will be the most important. If the objective is to acquire a holding in a venture-capital business, management quality will be essential. These ponderations are of interest not only because they contribute to a global measurement of the firm's quality, but also because they help to guide the assessment process. The meta-expert will use this knowledge to decide the order of the tasks to be executed.

— Within function j, weights p_{ij} are allotted to function characteristics by ponderation rules. These weights, on a 3-point scale, represent the observed importance of the firm's characteristics in assessing the quality of the function j, i.e. in determining the partial risk R_j. These p_{ij} ponderations may vary dynamically during the assessment process.

— The elementary risks, or r_{ij}, are assessed on a 5-point scale from "very low" to "very high", and result from the assessment of the characteristics.

— The degrees of judgement r_{ij} and their importance pij are aggregated at the upper level by judgemental experts in order to obtain partial assessments R_j. These partial assessments, and their importance g_j, are themselves aggregated at the top level to obtain a global assessment. The process is recursive and may be repeated as often as there are levels in the sub-domain hierarchy. This methodology enables traces of risk to be propagated and combined in declaratory fashion throughout the aggregation levels in order to arrive at a global risk. The different stages are illustrated in figure 1. The basic paradigm chosen to aggregate the judgements is that of multi-attribute decision models. They will be described in more detail in § 8.

This declarative approach has several advantages:

— the concepts are clear, expert reasoning is represented explicitely, knowledge is accessible and not represented in the form of probabilistic formulae.

— contradictory information is processed explicitely. For instance, if one characteristic suggests a high degree of risk while another suggests a low one, then the judgemental expert will choose between them by examining the weight of each characteristic.

— Knowledge is represented flexibly. It is unnecessary to describe every combination of characteristics and their values in the rule premises, as they are in most financial diagnosis systems. The risk of combinatory explosion in the number of rules is thus avoided. In our representation, if a new characteristic is added, then a further elementary judgement will be assessed and then quite naturally aggregated by the judgement model.

5 Architecture and operation of CREDEX

5.1 System architecture

The concepts of second generation system architecture were used to develop CREDEX. These systems are characterized in that control is distributed among several tasks and managed by meta-expertise, integration of experiential knowledge and of model-based knowledge [Fink 85], [Chandrasekaran 84]. This type of system was

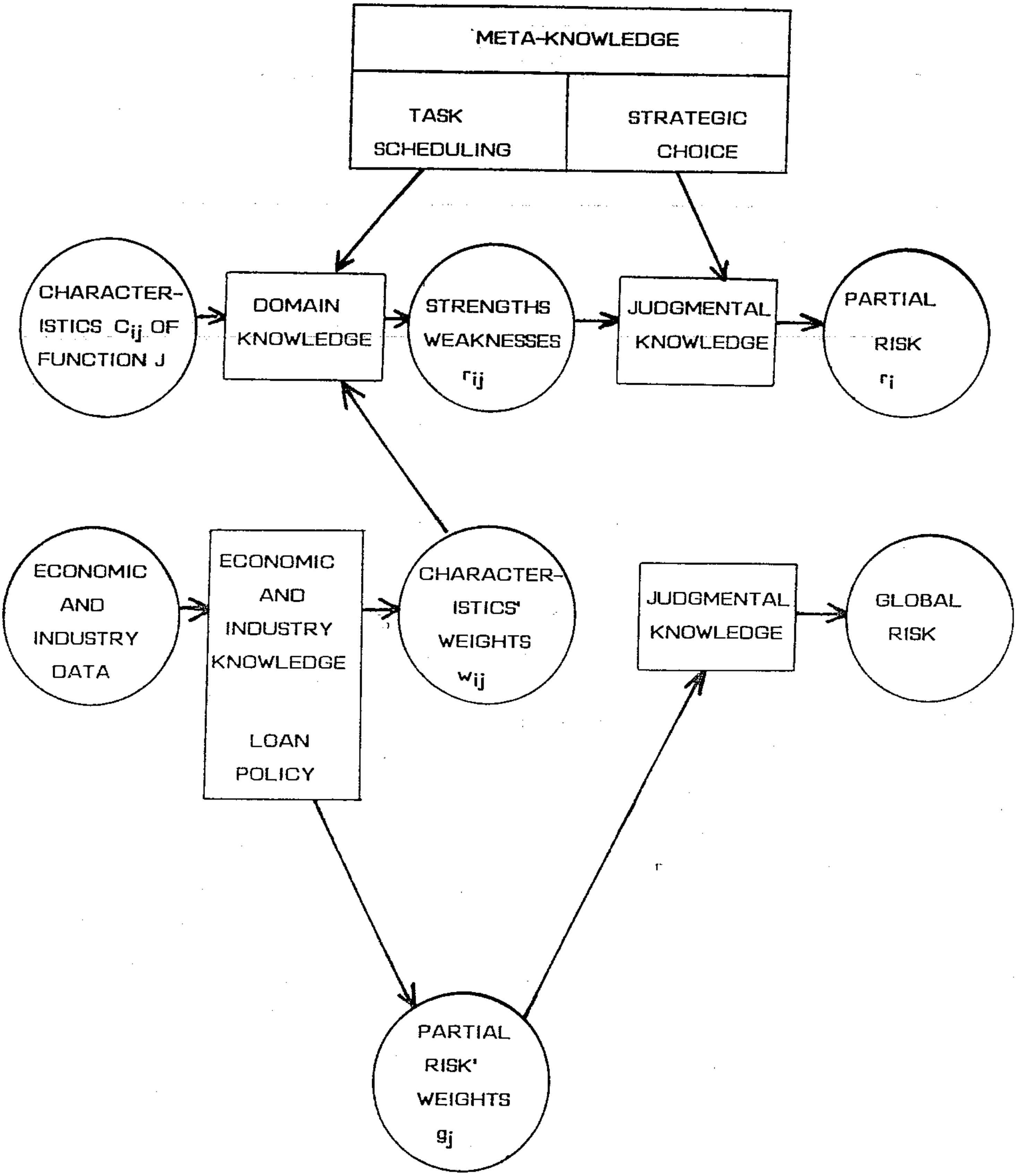


FIG 1 : PHASE EVALUATION STRATEGY

successfully implemented in physical system failure detection [Rieger 77], [Fink 84], [Genesereth 84], and in the medical field [Weiss 78], [Patil 81], [Xiang 86].

However, as Hart underlines, [Hart 86], [Reboh 86], the diagnosis aspect in financial assessment is not entirely like that in medicine, since no predetermined cases exist in illnesses, and diagnosis and judgment phases interact. General control strategy needs to be re-thought out. Moreover, Fink points out [Fink 85] that if domains other than physical or medical, which are those privileged by second generation systems, are to be explored, model-based knowledge should be represented differently from that of functional models.

The CREDEX system integrates both **experiential knowledge** of the domain (or surface knowledge) and **knowledge based on multi-attribute judgmental models**, in the form of independent experts. They are controlled by the supervising meta-expert on a higher level. [Pinson 88]. Each of the evaluation tasks is carried out by one of the three types of expert (Fig. 2):

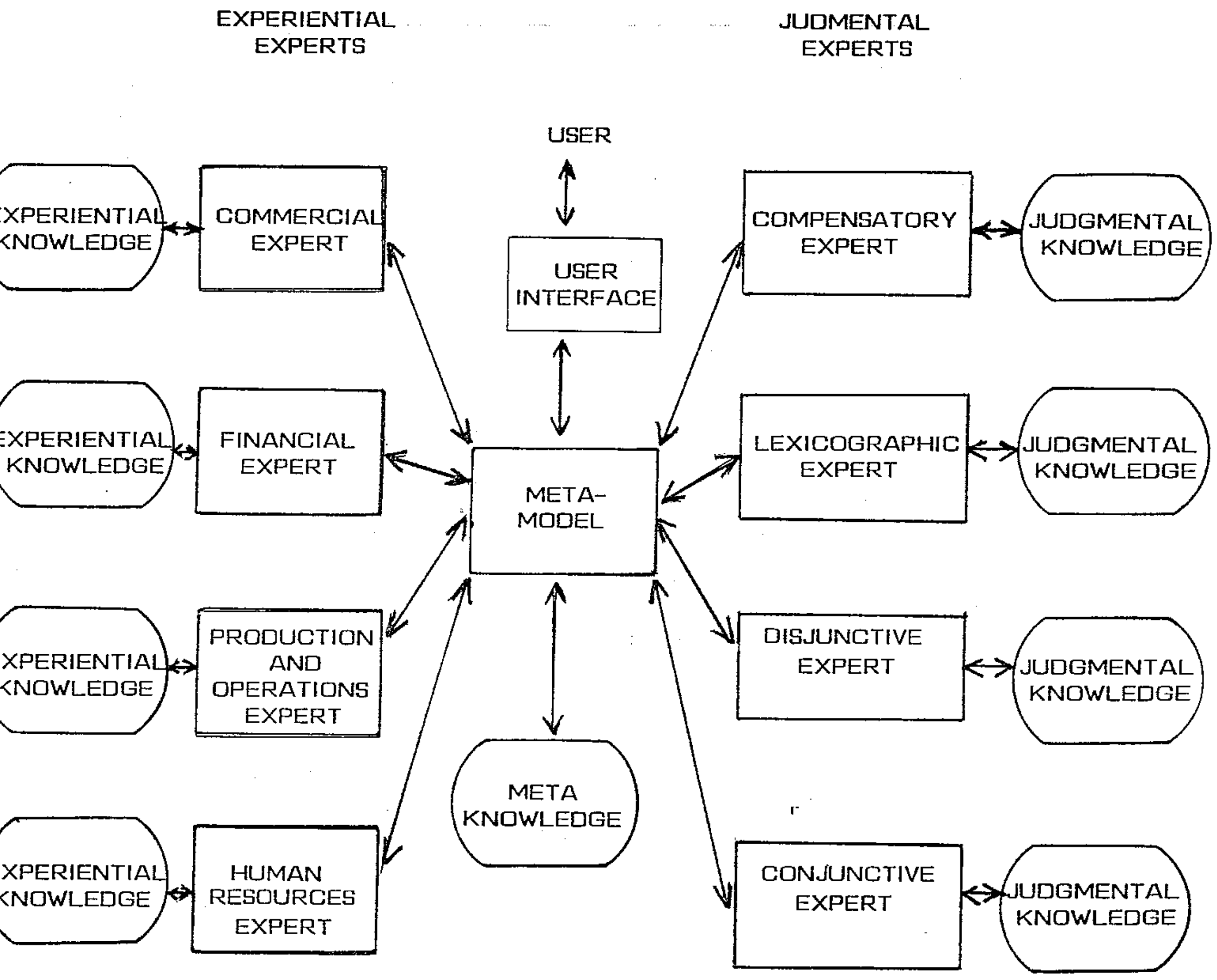
1) Experiential experts correspond to each sub-domain.
2) Judgmental experts correspond to each multi-attribute judgmental model
3) The meta-expert distributes control among the different experts and manages the problem-solving process.

Experiential experts deduce the importance p_{ij} of the sub-domain characteristics and make an initial assessment of the sub-domain in terms of strong and weak points and elementary associated risks r_{ij}. These inferences may suggest that further data should be acquired, thus changing the ponderation system.

Judgmental experts carry out deeper analysis. They contain general cognitive models of information processing. They examine the elementary risks rij and their importance pij and combine them into a partial risk RP_j through a set of general lexicographical, compensatory or conjunctive decision rules. The meta-expert is responsible for choosing the appropriate judgmental model.

The meta-expert is the control structure at the upper level [Chadrasekaran, 87]. It determines which expert should be activated. The experiential experts are activated in order of importance g_j. When one of the experiential experts has finished its evaluation task, the meta-expert chooses one of the judgmental experts according to the problem to be solved and hands it over.

FIG. 2 CREDEX ARCHITECTURE OVERVIEW



Each expert has its own knowledge base. They communicate among themselves by communication registers represented as a semantic network (Fig. 3). Here, the experiential experts store the inferred information; the judgmental experts then use the information to measure the quality of the sub-domain during the aggregation phase, in order to appreciate the overall quality during the synthesis phase. Finally, the meta-model uses this knowledge for its strategy choices and its decisions to stop the reasoning. [Pinson 87]. Each of the experiential experts cumulates the elementary risks rij according to their value and their weight. A number of medical expert systems are based on this cumulative process. [Mariot 86].

The CREDEX structure resembles a "blackboard" type model [Hayes-Roth 85], [Nii 86]. This is because we call the knowledge sources - both modular and independent - "expert", the control mechanism "meta-expert", and the common working memory, or blackboard, "communication registers". For each knowledge source, a set of predicates specifies the situations in which the production rules of the knowledge source will be triggered. The meta-expert chooses the knowledge source to be activated according to criteria such as priority, the importance of the sub-domains, the reliability of the data, and the complexity of the task. This focalisation process is not determined a priori, but used as and when the opportunity arises in the system reasoning process (opportunistic reasoning). It should however be noted that the hierarchical control structure of the "blackboard" model is here simplified: at the highest level, the meta-expert directly chooses a sequence of knowledge sources to be activated (cf. § 6.3), thus avoiding conflict resolution difficulties.

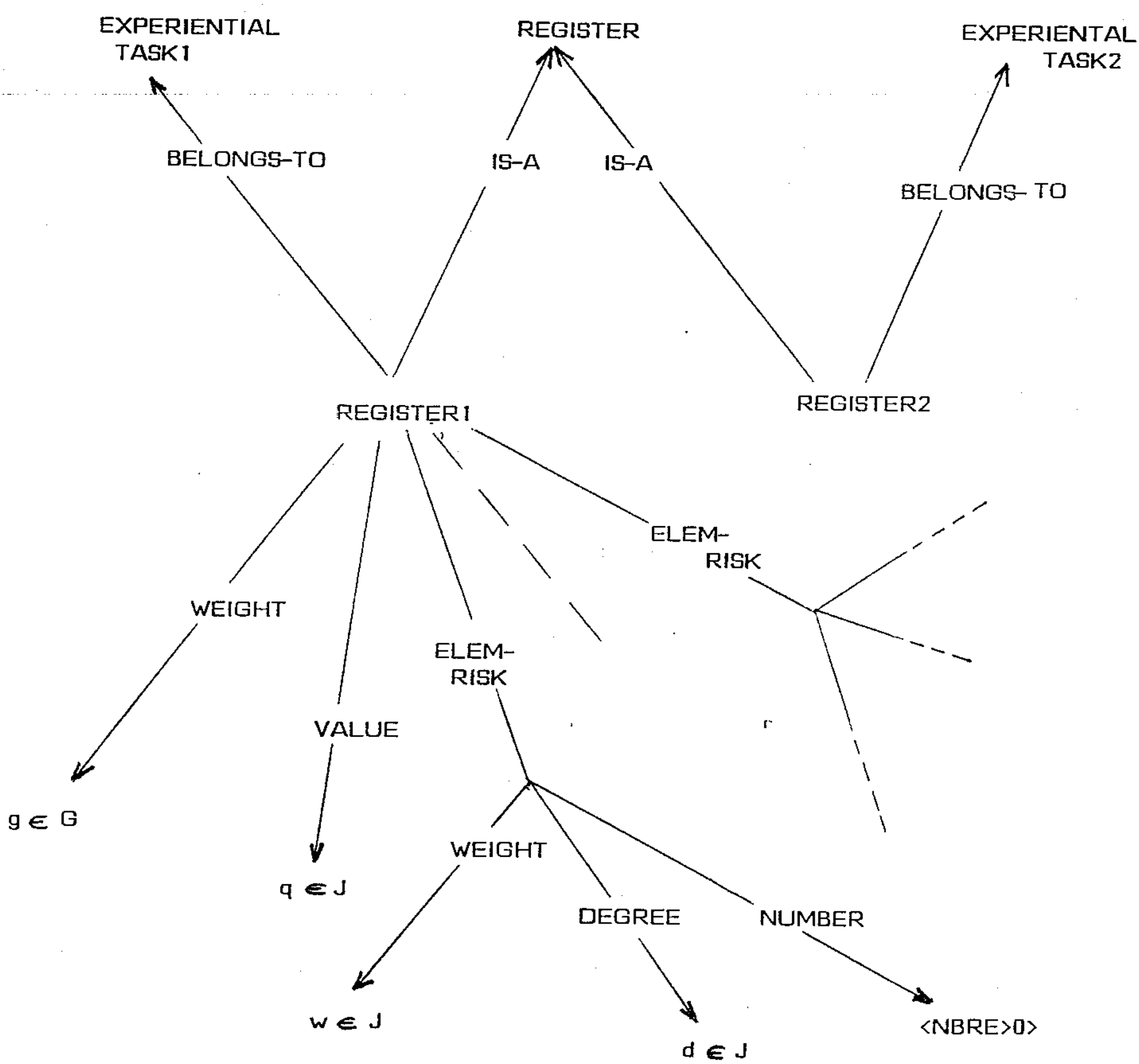
5.2 Knowledge representation

CREDEX is built on the SNARK inference engine and formalism [Laurière 86]. Knowledge is represented in first order predicate logic and in some cases, in second order logic. This is because SNARK language has some of the characteristics of second order logic, such as the facility to use predicate variables. Reasoning heuristics are formalized in classical fashion through production rules.

^ <condition on relations> +
---->
^ <conclusion>+

with <condition> : = R(x) <op> (y) where (x) and (y) are variables instantiable by the objects of the working memory and propagated in the rule conclusions. There are three

FIG. 3 PART OF THE COMMUNICATION NETWORK



types of operations in the conclusions and actions: 1) modification of the working memory by creating objects, relationships (action: CREATE), suppressing objects (actions KILL, KILLFACT, KILLFACTS), assessments of single-valued relationships (R(x)<--(y)) or multi-valued relationships (R(x) <== (y)), 2) request for information or written diagnosis (actions READ and WRITE), 3) modification of control by meta-actions EXAMINE, ACTIVATE, INHIBIT.

In the working memory, the properties of the objects, the associations between them, and statements are represented by associative triplets in the form <object relation value>, where "relation" and "value" can also be structured objects. This representation is closed to the schema one of SRL [Fox 84] since particular and generic objects can be created. This formalism makes the working memory isomorphic to a semantic network where inheritance properties, default values and transitivity can be defined by rules.

5.3 Reasoning mechanism

The CREDEX control strategy is mixed: it is both goal driven and data driven. This is the approach which most closely resembles the analyst's reasoning when he assesses a company's sub-domains, since his reasoning is driven by, and makes use of, all the available data to answer this question: given the known characteristics of the company applying for a loan, its activity sector, and the bank's policy, what company strengths and weaknesses can be deduced, and what opinion can be given of the company's health and the bank's degree of risk?

Since the task agenda is managed by meta-rules, the reasoning process can focalise on a given goal while the SNARK engine's forward chaining option enables deductions to be made from all **the available data** within a task. This control strategy is better adapted to our field than the backward chaining commonly used. This is because backward chaining supposes the formulation of hypotheses to be checked, or "typical illnesses", which is not the case in the field of corporate assessment. Moreover, when a swift answer is required, it is impossible to ask the user to supply all the data on the company by answering the system questions (MYCIN requires a 50-minute session to make a diagnosis [Ham 84]). The user must furnish **additional information** and be guided by the system when collecting information. The backward chaining method has proved artificial, aiming more at system efficiency, i.e. limiting the search space by focalizing on the goal, rather than at seeking for isomorphy between the model and the decision process.

5.4 Operating mode

CREDEX operates in two modes:

— **Diagnosis mode** (D mode): in this mode, every sub-domain is assessed in order of weight. A report indicating its strengths and weaknesses, and the system's appreciation of its risks, is printed for each sub-domain. When they have all been assessed, a final report, giving the overall appreciation in the form of a global risk, is produced.

— **Assessment mode** (A mode): assessment may stop mid-way if the stop heuristics can come to a swift global risk conclusion without going through assessment of all the sub-domains. The most important sub-domain is assessed first. If there is enough information for CREDEX to produce a global risk assessment, the system concludes without assessing the other sub-domains, thus inhibiting the corresponding tasks. Otherwise, the system continues to assess the next sub-domain. There are two advantages to this stop process: first, it reduces execution time, and second, it avoids pointless questioning of the user.

6 The meta-expert

When control is exercised by a meta-model, the knowledge of the domain and its operation model are both represented [Davis 80], [Lenat 83], [Pitrat 86]. The inference engine reasons uniformly either on the knowledge, i.e. at "object level", or on the control, i.e at "meta-level". While a"meta-level" is an intellectually attractive concept, few systems have so far put it into practice. This is because it is not always possible to reason at control level, since only the interpreter possesses the control information, which is therefore implicit and inaccessible.

In CREDEX, the meta-expertise has been put into an independent expert with its own knowledge base (the metabase), which serves as a supervisor. It has many activities:

— creating the data structure necessary for communication between experts;
— managing the task agenda and cooperation among experts;
— creating in dynamic fashion the operation graph according to the importance of each experiential task;
— choosing the judgmental expert to be activated according to the situational and environmental knowledge possessed on the task to be judged; and
— stopping the reasoning process when sufficient information has been gathered to make a swift global risk assessment.

6.1 Task definition

The meta-expert reasons not on domain objects but on tasks within the meta-domain. It manages several types of task:

— *experiential tasks* which assess sub-domains of the entity. In the case under study, there are four, representing the different functions of the company assessed: EVAL-CIAL, EVAL-FIN, EVAL-PROD, and EVAL-MAN named for the commercial, financial, production and human resources functions respectively.
— *judgemental tasks*, named for the judgmental models they represent. They encompass the most well-known models of cognitive psychology: the compensatory model is represented by JUDGEMENT-COMP, the lexicographical model by JUDGEMENT-LEX, the conjunctive model by JUDGEMENT CONJ and the disjunctive model by JUDGEMENT-DISJ.
— *the meta-task*, still known as **strategic task**: CHOICE-JUDG. It will be invoked after the completion of all experiential tasks and enables choice of the appropriate judgmental model.
— *the stop-task*: : the meta-expert calls for the CHOICE-STOP task after every judgmental task, to check if it has sufficient information to draw a definite conclusion.
— *sub-tasks:* some complex tasks are subdivided into sub-tasks, the execution of which is controlled by local meta-expertise.

Each task may have two states: ACTIVE and INACTIVE. The meta-expert knows when to activate or disactivate a task. The stop task has special status: it is activated if the user chooses the assessment mode (mode A), and disactivated for good if the user chooses the diagnosis mode (mode D).

6.2 Meta-relations

The meta-expert uses two types of relation: 1) meta-relations constituting the **static model** of the entity to be assessed; and 2) meta-relations representing its **dynamic model,** created by the meta-expert during its reasoning process.

The **static meta-relations** define the types of task and subtask managed by the meta-expert, and the hierarchy between them. These relations are to be found in the meta-expert's initial database. They are components of the semantic network illustrated in Fig. 4. For example, the specialization relation ISA (<task> <class>) between a task and its class in the commercial function will be written ISA (EVAL-CIAL, EXPRIENTIAL-TASK).

The static meta-relations represent the hierarchical model of the entity to be assessed. If a further sub-domain has to be studied, all that needs to be done is define the class it belongs to, the sub-tasks it may comprise, and its communication register. For instance, if the "distribution network" function requires explicit processing, then the following three relationships will be defined in the meta-expert's database (DISTRIB-RISK will be the communication register of the EVAL-DISTRIB task) :

EVAL-DISTRIB ISA EXPERIENTIAL TASK
DISTRIB-RISK BELONGS-TO EVAL-DISTRIB
DISTRIB-RISK TYPE RISK

CREDEX will automatically take account of this extra task in its assessment of the global risk.

The **dynamic meta-relations** created by the meta-expert enable the reasoning model to be built. In the systems managing the tasks, time is usually represented in two ways. First, **absolute specification** of when a task starts and what its timespan will be. Second, relative specification of the way activities precede or follow on from each other. In CREDEX, only the latter, i.e. **ordinal specification** of time is of interest. We chose to represent precedence relationship between tasks ta_i and ta_j by NEXT-OPERATION (ta_i, ta_j). It is created dynamically from the WEIGHT (ta_i, g_i) relation, which attributes weight g_i to task ta_i (g_i s' are given to the system interactively by the user, or are assessed by the meta-expert), and from NEXT (g_i, g_j) which establishes a total order relation among the task ponderations, eg. NEXT (VERY IMPORTANT, IMPORTANT). These relationships are vital to the meta-expert's reasoning when the gj symbolic values are processed.

To give an example, if the user decides that the commercial function is very important, and that the financial function is important, the meta-expert creates the WEIGHT (EVAL-CIAL, VERY-IMPORTANT) and WEIGHT (EVAL-FIN, IMPORTANT) relations. These relations, coupled with the order relation NEXT (VERY IMPORTANT, IMPORTANT), will enable the meta-expert to create the NEXT-OPERATION (EVAL-CIAL, EVAL-FIN) relation.

6.3 Meta-rules

The system uses strategic meta-knowledge to build the best resolution strategy for the case in question. The meta-expert uses several types of meta-rules to help it choose.

Meta-rule for agenda management : task scheduling is the main work of the meta-expert, as the operations graph (Fig 4) shows. It puts tasks in the agenda according to their priority. Meta-rule DEMO1 is a "super-demon" rule having absolute priority. It is like this:

As soon as an experiental task is activated, first examine the rules for execution, then the strategic task of choosing a judgemental model, then the rules which will judge the task, then the rules for possible conclusion, and finally the activation/disactivation rule.

The engine calls on this agenda scheduling meta-rule after each transition between one experiential task and another.The context in which the rules for each task are executed is defined by the following premise:

ISA <task> = <class>

where <class> designates the context of the task. For example, ISA EVAL-CIAL = EXPERIENTIAL-TASK is the first premise of the commercial task rules. The concept of context was represented in the CENTAUR system [Aikins 83] in the form of a "frame" in which certain "slots" contained the rules concerning them. The major disadvantage here is that rules are supplied by name and not by content, thus making modifications very difficult.

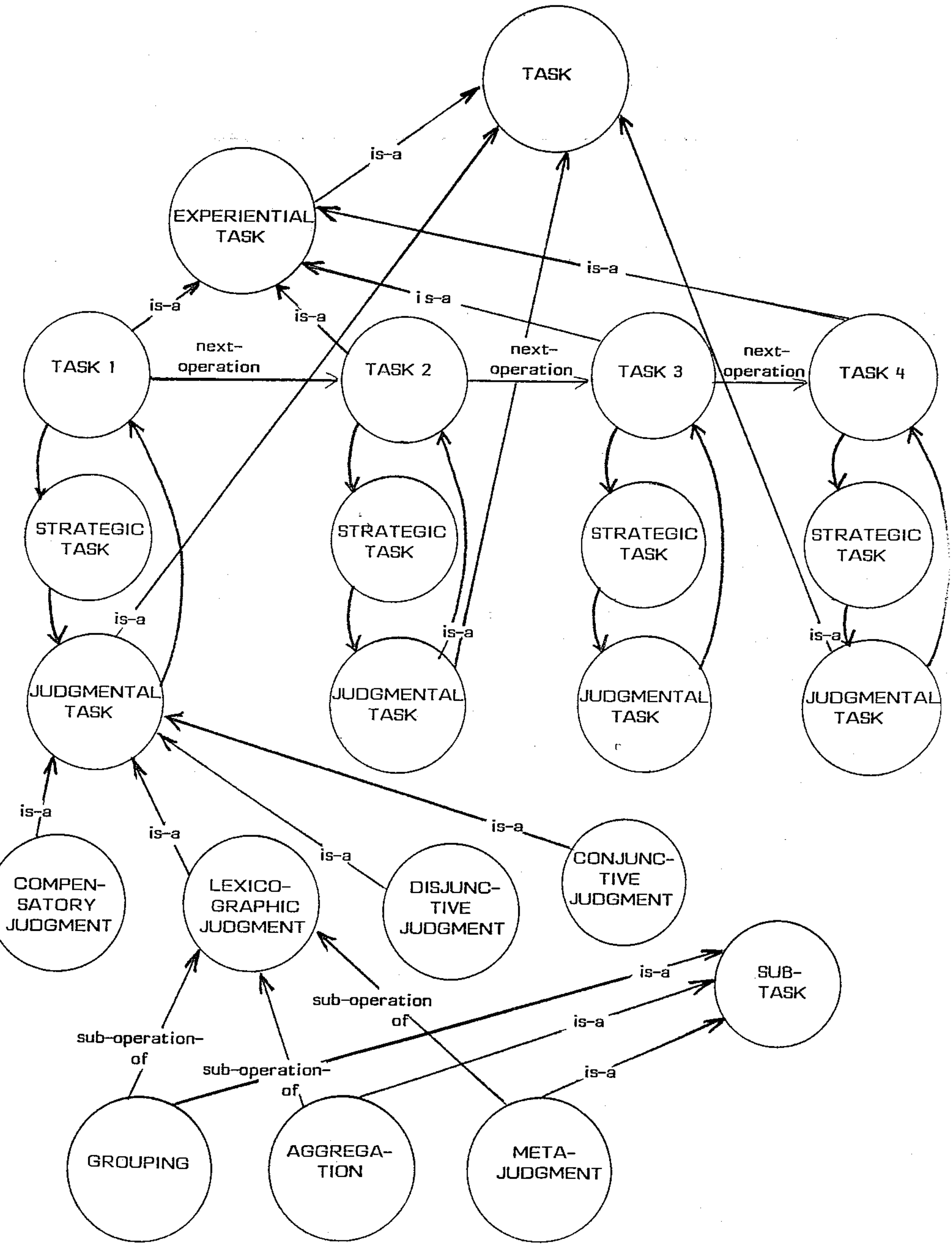
In CREDEX, task classes or contexts are EXPERIENTIAL-TASK, STRATEGIC-TASK and STOP-TASK. These contexts are invoked in meta-rule DEMO1 when an execution priority is being dealt with. For instance

```
EXAMINE (R1)
PRIORITY (R1) 1
ANTECEDENT (RI) : ISA(X) = EXPERIENTIAL-TASK
```

The engine will only start off the task if the STATE (<task> ACTIVE) predicate is true. It is in true value in three different ways:

1) It is switched to true by the activation/disactivation meta-rule for experiential tasks, in accordance with the operations graph.
2) It is switched to true by the strategic choice task for judgemental tasks.
3) It is switched to true for the stop task by initialisation rules if the assessment mode (mode A) is chosen by the user.

FIG. 4 : OPERATIONS GRAPH



4) It is always true for the strategic choice task, which should always be invoked after the experiential task , in order to choose the appropriate judgemental task.

Meta-rule for task graph construction : when he is assessing an entity, the analyst has his own utilisation model for the knowledge he expresses, in the form of ponderations of the tasks to be executed, which will be represented by the meta-expert in an operations graph (Fig. 4). The operations graph is created by the following meta-rule:

for ta_i, ta_j e {experiential task} such that
NEXT (WEIGHT (ta_i)) = WEIGHT (ta_j)
---->
task ta_j has to be activated after task ta_i.

Meta-rule for direct task choice : the most important experiential task is chosen by the meta-expert as the initial state of the graph:

first activate the most important task

The maximum permitted ponderation is one of CREDEX's parameters. It is defined by the relation MAX-WEIGHT (VAL, VERY IMPORTANT) which is one of the meta-expert's initial data.

Meta-rule for task activation/disactivation : when the active experiential task ta_j has finished its work, it is disactivated, along with the judgemental task ta_k which assessed it. The next operation is activated in the order on the operations graph, and a new assessment phase starts.

for ta_i , ta_j e {experiential task} such that
task ta_i is active,
the next operation to be activated is ta_j
for ta_k e {judgemental task} such that
ta_k is active
--->
disactivate ta_i and ta_k
activate ta_j

The activation/disactivation rule is a local "anti-demon", i.e. a rule which should only be triggered when no other rule of the active task is triggerable. This is why it has lowest priority in the agenda management meta-rule.(priority 5, if priority 1 is highest).

Decision to stop reasoning: the meta-expert has the knowledge concerning inference stop and conclusion. Meta-task STOP-CHOICE takes this decision, which is invoked after assessment of each experiential task. It examines the judgement of their quality. For instance:

If the quality of the most important sub-domain is very poor, conclude that the quality of the entity is very poor and stop inferences.

The meta-action which stops reasoning has two advantages: 1) it avoids pointless questions since tasks of no interest are inhibited; 2) it improves system efficiency since the assessment process stops as soon as the system is able to conclude.

Choice of judgemental models: the meta-task which chooses judgemental models reflects the cognitive process of the expert in a decision-making position. Each judgemental expert represents a completely different multi-attribute assessment process (see § 8). The meta-expert has the knowledge with which to choose the most suitable judgemental strategy for the problem to be judged. It chooses by taking into account environmental (loan size, market competition, etc...) and structural factors such as the complexity of the task, reliability of the data, etc.
The strategic task is placed in the agenda by the meta-expert's super-demon rule DEMO1, using meta-operation EXAMINE:

```
EXAMINE (R)
PRIORITY (R) 2
ANTECEDENT (R): ISA choice-judg = strategic task
```

Because it has priority 2, this task will appear after the experiential task, which must be judged and which is of priority 1.

7 Experiential experts

The experiential experts appraise sub-domain characteristics in terms of risk elements r_{ij}, and establish a ponderation system p_{ij} of these characteristics. Each expert represent a reasoning task based on surface knowledge. In this type of expert, the knowledge used is of the relational type, connecting the values of the characteristics and the likely risk elements. As far as corporate assessment is concerned, four experts corresponding to the four main functions of the company are used: the **commercial expert** analyzes the quality of the commercial function, the **financial expert** assesses financial and accounting data, the **production and operation** expert handles production, research and development data, and the **management expert** assesses the managing team and capital structure.

The objects and statements of each sub-domain are respectively defined as "frames" and predicates. For instance, the commercial expert possesses two types of "frames": "product" type objects and "clientele" type objects. The financial expert manipulates more complex objects because time is included in its representation; this gives objects such as "indicator", "yearly results" and their cartesian product "indicator x yearly result". For instance, the ratio between fincancial expenses and net sales is represented by:

```
(FF/CAHT (ISA indicator) (weight important)
    (value $001)(value $002)
    (variation $003)(evolution $004)
($001 (date t1)(val v1))
($002 (date t2)(val v2))
($003 (val a%)(date-start t1)(date-end t2))
($004 (val increase)(date-start t1)(date-end t2))
```

We have added the attribute WEIGHT, representing the importance of the object in the assessment process of the function's quality. Some relationships are initial facts from the database; others are dynamically created by the expert during its reasoning and enrich the working memory: this is the case for the LIFE-CYCLE (<product> <value>) relation and the multi-valued relations EVOLUTION and VARIATION.

Each experiential expert has its own rules base which represents sub-domain assessment and diagnosis expertise. The general structure of these rules is the following:

ISA <experiential task> = experiential task
state < experiential task> = active
^ < condition on relationships > +
--->
^ <conclusion> +

The first premise defines the context in which the rule will be applied: the rule belongs to the experiential task <experiential task> (eg., this premise is ISA EVAL-CIAL = EXPERIENTIAL TASK for commercial task rules). This context is used for meta-rule DEMO1 to place the experiential task in the agenda. The second premise triggers the rule, which will occur if the experiential task is active. The remaining premises test the characteristics of the sub-domain. The conclusions are : 1) requests for further information, 2) insertion of ponderations, 3) elementary risk assessment, 4) elements of diagnosis, 5) switching the focalisation predicate to true, and 6) memorisation of the calculation results.

Semantically, these rules belong in five main categories:

– **Rules for insertion of ponderations**: ponderations may be by default (eg, the debt ratio is always important), ponderations assessed by the experiential experts at the start of the reasoning (eg, the weight of product X depends on its net sales), and ponderations assessed dynamically depending on the context (e.g., if working capital requirement is analyzed, then client's average collection period, inventory turnover and supplier's payment period are important). A rule which weights a product heavily will be written as follows:

Rule: IMPORTANT-PRODUCT
context *1) the rule is a rule from the commercial expert*
2) the commercial function assessment task is an experiential task
trigger *3)the commercial task is active*
4) for all products belonging to the set of commercialized products
tests *5) the product's net sales is important*
6) there is a dominant product
conclusions –this product is important for the company
–memorize the ponderation of this product in the "product" frame of the commercial expert database.

– **Characteristics assessment rules**: these rules concern judgements on the quality of the company's characteristics, and count up the strong and weak points in risk elements. They act by updating the communication registers between experts. As an illustration, here is a rule from the commercial expert which is assessing a positive element:

Rule: STRONG-POINT
context *1) the rule is a rule from the commercial function*
2) the commercial function assessment task is an experiential task
triggers *3) the commercial task is active*
4) it possesses a communication register called CIAL-RISK
tests *5) for every product (xprod) commercialized by the company*
6) such that (xprod) contributes to margin
7) such that the (xprod) growth rate is rising
8) product (xprod) has (p) importance
conclusions –count a low risk element of weight (p)
–memorise this information in the appropriate triplet of the commercial risk register.

These are the commonest rules and they represent the domain judgmental expertise.

– **Rules requesting further information**: at the start of the reasoning process, the system asks for the basic information. Afterwards, it acquires information from necessity and creates the relationships it needs for its reasoning. For instance, the management expert's PARTNER rule asks if the director would accept outside help if more finance were needed:

Rule: PARTNER
context 1) the rule is a rule from the management expert
trigger 3) the management task is active
tests 4) extra finance is needed
conclusions –ask if the company directors are prepared to accept partners with cash injection
– memorize answer in "director" frame of the management expert's database

– **Ratio calculation rules**: if the accounting data is known and present in the knowledge base, these rules create and calculate the various financial ratios needed by the system to pinpoint the strengths and weaknesses of the financial function. These are calculated for each yearly result. This expertise, which is specific to the financial function, represents and manipulates time as separate and adjoining intervals.

– **Interpretation rules:** these ones, like those above, are specific to the financial expert. They serve to make a spatial and temporal study of financial indicators in terms of levels and evolution. To study the improvement or worsening of a company's situation, it is not enough simply to compare a ratio with a threshold. Evolution between an initial and a subsequent period must be studied, and the latter must be included in the system's parameters. These rules form the bridge between assessment of the characteristics and their appraisal in terms of risk elements.

Focalisation rules: Some rules belong to a particular context. If that context is activated, the system will focalise the reasoning process on it and trigger the relevant rules. This mechanism, which is common in artificial intelligence, gives detailed analysis of particular situations and avoids unnecessary questions for the user. For instance, the system has the following rule:

If the difference between the working capital requirement and the working capital is not covered by account receivables, a detailed study of the working capital requirement must be made before drawing a risk conclusion.

This type of rules sets up a hierarchy of reasoning to analyze a bad situation, find the causes by questioning the user, suggest solutions and modulate risk elements.

8 Judgmental experts

Judgmental experts combine risk elements r_{ij} while taking account of their weight p_{ij} in order to produce a degree of partial risk RP_j for each sub-domain. The partial assessments, together with their weight g_j, are aggregated in their turn on the upper level, to arrive at a global assessment. In CREDEX, the meta-expert chooses from four judgmental experts: the conjunctive, the disjunctive, the compensatory and the lexicographical experts. These experts represent multi-attribute information processing models commonly proposed in cognitive psychology and in decision theory [Einhorn 81]. Each model supposes a totally different assessment process:

The conjunctive model starts from the supposition that, for an entity to be judged acceptable, all its characteristics must have scores above a certain threshold. If this is applied to risk analysis, the model supposes that every risk element r_{ij} of sub-domain j must be below an a priori fixed threshold s_j.

The disjunctive model is called the "maximum evaluation function", since the entity is judged on its best appearance. In terms of risk analysis, a very-low risk element r_{ij} is sufficient for a "good quality" conclusion on the sub-domain.

The compensatory model: the positive judgments made of some characteristics compensate for the negative judgments made of others. An adding or multiplying function aggregate all the judgments, together with weights of characteristics, to produce a global score.

The lexicographical model supposes that attributes are examined sequentially, starting with the most important. If a conclusion can be drawn, the assessment stops. Otherwise, the attribute next in order of importance is examined. As regards risk analysis, highly important risk elements r_{ij} are first examined to deduce the sub-domain quality. If the system can conclude, it stops assessing the task and goes on to the next one.

After research in psychology on the use of these different models, different choice factors.emerge. In CREDEX, we have retained two kinds of factor: 1) structural factors inherent in the task to be assessed, i.e, the complexity or the quality of the information possessed by the system, such as reliability, or missing data; 2) environmental factors, i.e. the degree of risk observed, the size of the loan, the loan portfolio, market competition, etc. This knowledge is formalized in the judgmental model-choosing meta-task, also called strategic task. When it is activated, it puts the most suitable judgemental model into the agenda.

9 Protocol for CREDEX operation, and results

As mentioned earlier (§5.4), the system operates on two modes: Diagnosis (D mode), which gives a final report after each function of the company has been diagnosed, and Assessment (A mode), which, using specific heuristics, can draw swifter conclusions on the company's quality without analyzing every function.
At the start of the session, the system asks the user questions about:
– the operating mode: diagnosis or assessment (D or A)
– the entity to be assessed: name, type, sector
– the assessment period: initial or ultimate yearly result
– the ponderation method for the company's functions: ponderation by default or explicit ponderation by the user.

During the reasoning process, the system guides the user through a logical sequence of questions on the company, formulates and prints out elementary diagnoses on each company function, prints out a quality judgement on the function, recommends action to be taken to improve this quality if possible in the case under analysis, and finally prints out a global qualitative judgement of the company in terms of corporate risk. To illustrate this, part of the assessment session on a small parts firm is annexed below.

The system is still in process of being validated. For the moment, we have tested it on some ten imaginary and real loan applications for small industrial firms. This sector was chosen because, contrary to the service or distribution sectors, for instance, the production and operations function in these firms is well-developed. The four functions are therefore all present. The results correspond to the experts' opinions, being slightly more conservative. This is due to the objective character of the system, which does not attenuate negative results by subjective factors such as personal relationships between the analyst and the client.

CREDEX has about 300 logical rules in the first order, over half of them being for the experiential experts. The number of rules is not significant in itself, although it is often suggested that it indicates the knowledge base's size. This number is in fact governed by the formalism chosen to represent the knowledge. First order logic means that the number of rules falls considerably when the domain can be modelized in the form of many similar objects belonging to a small number of classes. We have seen that corporate assessment corresponded to this type of modeling. The CREDEX rules thus reason on object classes.

The session is executed in 6-8 seconds on an IBM 3090 computer under MVS, when D (diagnosis) mode is used, and in 1.30 seconds in A mode (assessment), and the file under examination is an obvious case where stop heuristics are used. This speed of execution is due, first of all, to the efficiency of the SNARK engine, and second to the use of meta-knowledge, which enables the reasoning process to focalize onto the relevant tasks. The variations in execution time in D mode are due to the greater or lesser complexity of the company to be analyzed. For instance, if the system has to seek the causes for an excessive working capital requirement, and suggest actions to reduce it, the corporate assessment will take longer. Moreover, the longer the period to be analyzed (two, three or four financial years), the more time CREDEX will need to create the semantic network of financial ratios for each financial year.

10 Conclusion and further research

We have aimed to design a new expert system architecture integrating meta-knowledge, knowledge of the domain and knowledge based on judgemental models. This kind of approach is, indeed, vital in fields such as corporate assessment where the reasoning process is one of phases, and where several types of knowledge must be combined. The CREDEX system demonstrates the feasability of a multi-expert approach driven by a meta-model, in the assessment of credit risk. This multi-level structure combines two types of knowledge: experiential knowledge (or surface knowledge) to detect the strengths and weaknesses of the entity to be judged, and deep knowledge based on multi-attribut information processing models. The advantage of using a meta-model to represent the analyst's strategy on the upper level means that systems can easily adapt to a whole series of problems. As far as firms are concerned, the system can adapt both to small and large firms, and just as well to credit analysis as to purchase of holdings in venture-capital firms. The ponderation system means that the relevant weights and characteristics of the entity to be assessed can be modulated.

Further research and improvements should include:

– Extended knowledge bases for each experiential expert. For instance, the financial expert could take account of data on the funds flow statements, and of financial movements. Knowledge of bank policy could be reinforced by considering the way movements and assistance are spread out, what quality the banking pool is, and how the company account works. These extentions cause no theoretical difficulty since CREDEX has a completely modular structure. However, a considerable amount of time, and the availability of the experts, are necessary.

– Explicit consideration of the risk caused by lack of information about certain corporate aspects. In present systems, missing information is replaced by an averaged value of the characteristic concerned. This, while a simple solution, may hide a real risk element.

– Sensitivity anlysis, i.e. ajustment and refinement of the ponderation system and of the degrees of risk elements when the results do not satisfy the human experts. This is inherent to the validation phase and to studying the way the system stands up to variations in degrees of risk.

–Interfacing with the bank's files on client companies. In its present version, the basic data of the company are stocked in the database of each experiential expert of CREDEX. Not only will this improvement enable the system to get its information directly from existing files, but it will also enable the bank to make simulations on the possible risks in granting credit, and, using results, to apply for low-risk loans.

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