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MODELING, MEASUREMENT AND ARTIFICIAL INTELLIGENCE – TOWARD THE NEW GENERATION OF INTELLIGENT MEASURING SYSTEMS[1]

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Abstract

The most important contribution of the recent research in measurement was that the measuring equipment is involved in the information processing and that instruments are actually specialized computer systems. Design of the instruments is seemingly a straightforward task, however, complex measurement problems are ill-conditioned and knowledge-intensive. Considerable portion of the measurement related knowledge is in such problems heuristic and non-analytic in character. To evaluate it and to inject it into the measuring system design require symbolic approaches developed in artificial intelligence field. In consequence complex 'intelligent' measuring systems are coupled numerical-symbolic hybrid systems, with the knowledge intensive (expert) component cooperating with extensive numerical libraries. Such systems can even be embedded in other architectures designed for more abstract goals.

Keywords: intelligent measuring systems, coupled symbolic-numerical systems, 2nd generation expert systems, agents.

1. Introduction

Recent research made it finally plain that the measurement provides means of the acquisition of empirical knowledge, whenever knowledge available a priori is not good enough to create an accurate mathematical model. The development of a wider notion of measurement, applicable to cases when

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the measurement scale is not ordinal, led, in consequence, to the formulation of a new formal measurement theory (FINKELSTEIN, 1994; KAPOSI et al., 1993). The most important recognition, however, was that the measuring equipment is involved in the information processing at various levels of abstraction, and that at least from this point of view instruments and computer systems are alike, more to the point that instruments actually are specialized computer systems.

Designing instruments for smaller problems is a straightforward and routine task. Every field of science has its developed measurement technique and metrology to deal with the usual and smaller scale problems. Complex measurement tasks, especially those coming from interdisciplinary problems, are harder to tackle. They usually are ill-conditioned in a sense that a good design should be based a priori upon conclusions available in detail only a posteriori from the measured empirical knowledge, and of course such tasks are knowledge-intensive, see *Fig. 1.* (DOBROWIECKI et al., 1994). A really good planning of the experiments, resolving designing trade-offs, providing sound implementation, etc. requires an extensive insight into, and the maintenance of knowledge.

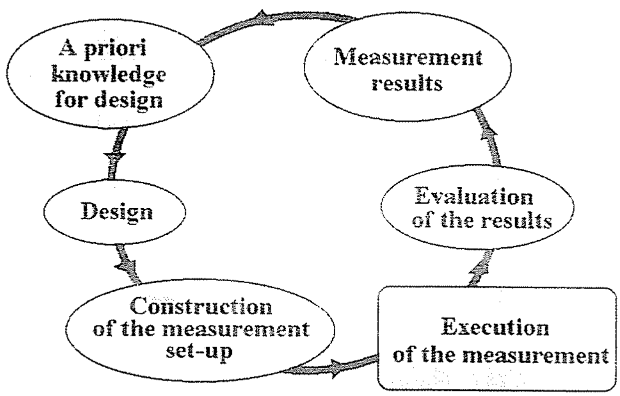

Fig. 1. Why advanced measurement is an 'ill-conditioned' problem.

2. Measurement and Knowledge

The distinctive characteristics of the expert knowledge in measurement are its considerable volume, diversity and complexity. To solve measurement problems (i.e. to provide the analysis of the problem and the synthesis of the measuring tool) an expert must draw, among others, from his knowledge about the measuring instrumentation, system modeling, about the interaction of signals and systems (signal and system theory), system identification methods, software packages, and many additional issues (LOUAGE et al., 1994a; LOUAGE et al., 1994b). In order to be successful such a person should also possess a deep physical insight and general planning skills to organize experiments, and to make a proper choice between different implementations and goals. A considerable part of such knowledge could even be based, or rather should be based, on experience about various border and problematic cases and also upon a kind of physical 'common sense' how to deal with the physical aspects of the instrumentation, and other environmental problems, see *Fig. 2*.

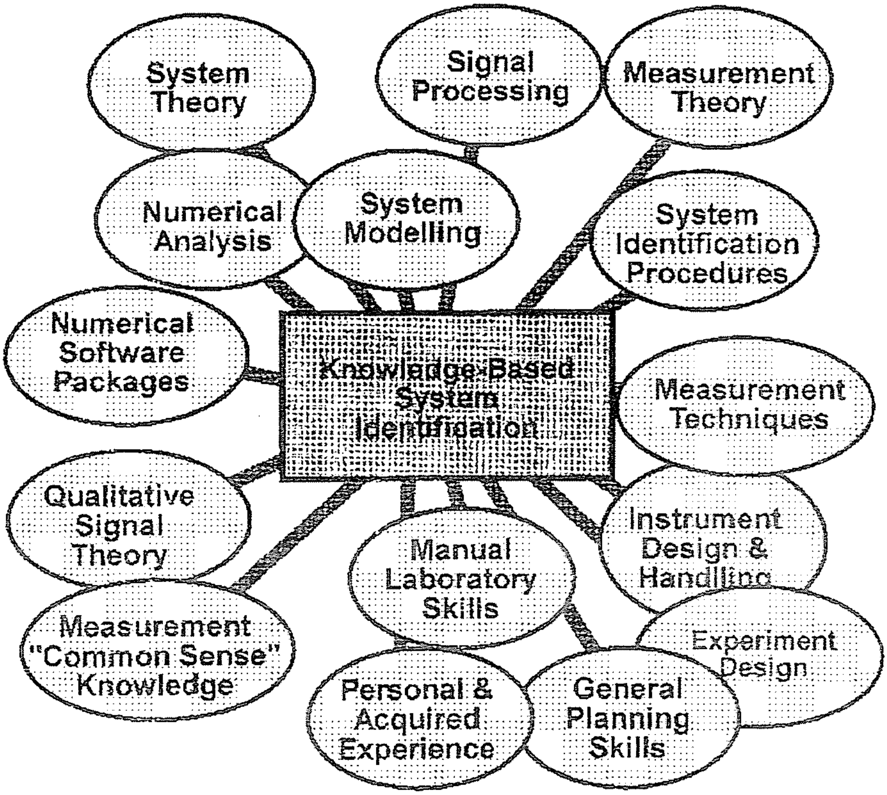

Fig. 2. What a measurement expert should know.

The reader should note that in measurement an expert formulates his knowledge in terms of more or less formalized models, and certain aspects of the measuring system design are strictly based upon the transformation and derivation of various mathematical models. Heuristic knowledge can be also expressed as models, but to do this we must enter the realm of symbolic information processing and generally that of artificial intelligence. It does not mean, of course, that our aim is to design systems to be 'intelligent', it is rather that for a moment only that field provides tools to tackle knowledge-intensive non-numerical problems (ZINGALES et al., 1991; LOUAGE et al., 1994a; KAHANER, 1992; DOBROWIECKI et al., 1994).

Measurement in general, but especially system identification (SI), exhibits a variety of 'typical AI' tasks, like decision making, design, interpretation, planning, diagnosis, etc. (ZINGALES, 1991; LOUAGE et al., 1994a). The knowledge how to do them well is available from the literature only in part. Only recently the related publications have begun to admit the importance of the heuristic decisions and the symbolic reasoning as a model of the professional decision making, which is always present in the maintenance of the measurement (GENTILE et al., 1990; HAEST et al., 1990; MEIER ZU FARWIG et al., 1991).

Complex 'intelligent' measurement systems are, by necessity, coupled numerical-symbolic hybrid systems, where the knowledge-intensive (expert) component cooperates actively with extensive numerical libraries. In control, monitoring and similar applications, i.e. where the measurement results and the model computed from them serve still other goals within the system, the coupled system will be even embedded (hidden) in the architecture designed according to a wider specification, see *Fig. 3.* (DAWANT et al., 1991; HIGHLAND, 1994; LOUAGE et al., 1994b).

3. Knowledge-Based Measurement Technology

Measurement contributes to artificial intelligence (AI) with a spectrum of interesting and stimulating applications, where new AI tools (representations, reasoning schemes, handling of uncertainty, etc.) can be effectively used and verified. A particular characteristic of the measurement, as a problem, is a continuous shift from the qualitative heuristic knowledge toward strictly analytic (algorithmic) models, or using AI related notion, from the 'shallow' toward the 'deeper' knowledge.

In the following we attempt to review how the knowledge-based methods are used in the measurement technology. First we will deal with the 'established' techniques resulting in 'standard' expert systems. Then we will consider the implications of the automation of the full course of experiments, finally we will review how the measurement would gain from some of the newest developments, see *Fig. 4*.

Until recently rule-based systems were the standard choice of architecture in any AI system development. Similarly to other application fields, rule-based systems in measurement were used mainly as advisory systems to choose sensors, instruments or processing modules, and as result interpreters in more complicated situations (COOK, 1993a; COOK, 1993b; EL-HAMI et al., 1994; FINKELSTEIN et al., 1993; MIRZA et al., 1990; ROWLAND et al., 1993; VANDER et al., 1991).

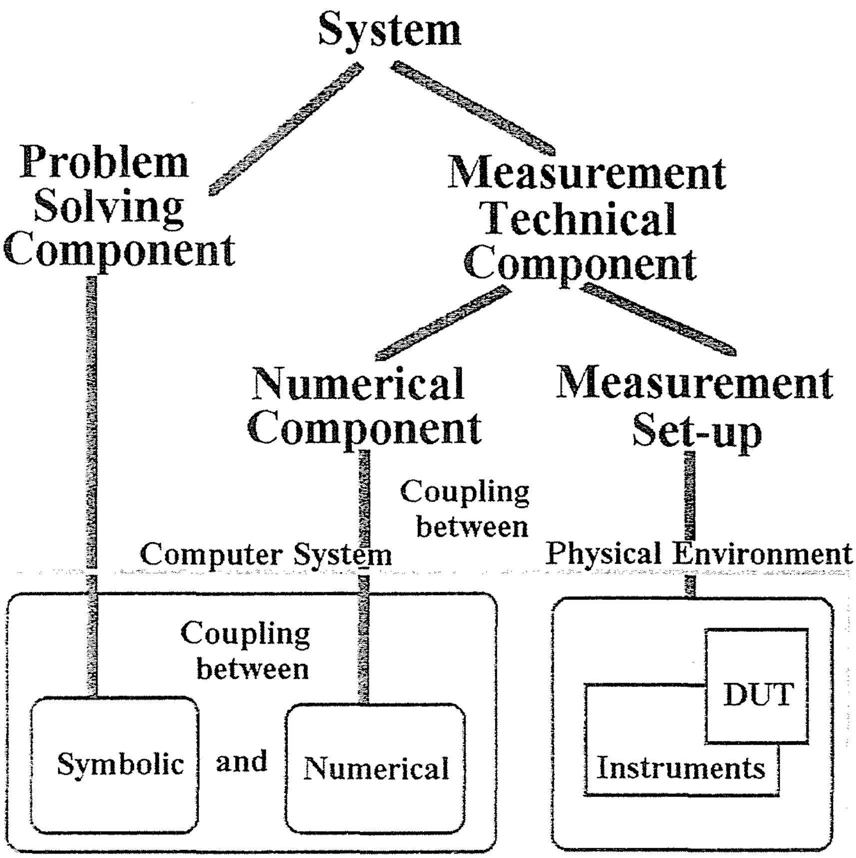

Fig. 3. General architecture of an intelligent measuring system

Actual and advanced research in measurement moved toward the automation of the measurement process. Measurement is the kernel activity of any kind of inductive modeling. Knowledge collected in the preliminary phases of the modeling serves as a basis to design experiments, and the corresponding measurement results are injected back into the model to improve its accuracy. Consequently, the logical step to take was to automate the design of the experiments, working with real signals and systems (SZTIPÁNOVITS et al., 1984).

Signal and system properties, furthermore, certain elements of the system theory belonged to the knowledge bases of some of the existing rule-based systems, those systems, however, could never execute measurements and acquire better signals to improve the quality of their reasoning. A system actively designing the experiments should, first of all, be coupled to the

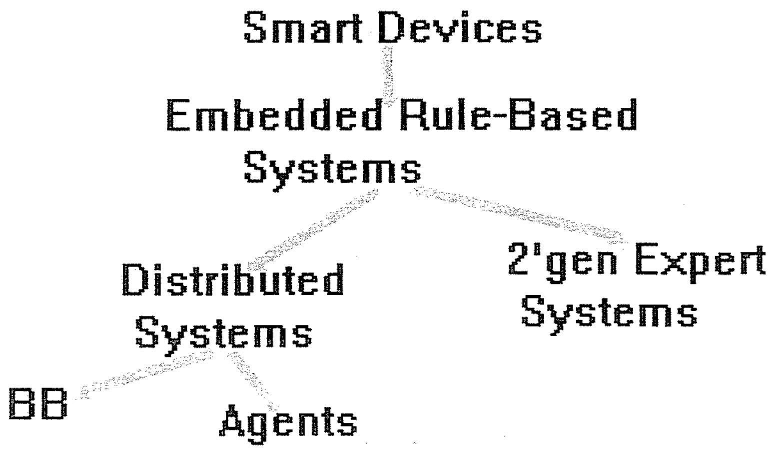

Fig. 4. Development of the AI architectures

measurement hardware (*Fig. 3*), must reflect the properties of these peripherals in its knowledge base and must be able to configure and to control them according to the developed plans.

Management of the experiments requires the maintenance of a full spectrum of information shown in *Fig. 2*, and it is just too complex for the traditional rule-based systems. The monolithic and homogeneous knowledge representation and rigid context independent control scheme of the rule-based systems made them utterly unsuitable for such purposes. For the worse artificial intelligence had nothing else to offer for a long period of time.

Black-board architecture, the only serious development beside rule-based system, could provide the solution if only certain questions related to the heterogeneous knowledge and opportunistic control of reasoning would be easily and effectively solved (CARVER et al., 1994). Black-board architecture suffers, however, from the same problems as the rule-based systems and, consequently, brought no breakthrough to the advanced automated measuring system design.

Slowly new ideas have emerged, replacing the rigid rule-firing regime with an architecture based upon the concept of so-called generic tasks and models (DAVID et al., 1994). Task tree reflects the insight into the structure and the interactions within the problem (*Fig. 5*). Tasks accept and output models which gradually converge to the full solution of the problem. Tasks and models should be, in a sense, 'standard' (generic), which reflects the common knowledge processing structure of many seemingly distant applications.

The approach lacks for a moment developed design technology, even that of the rule-based systems. On the other hand, it is totally open to the

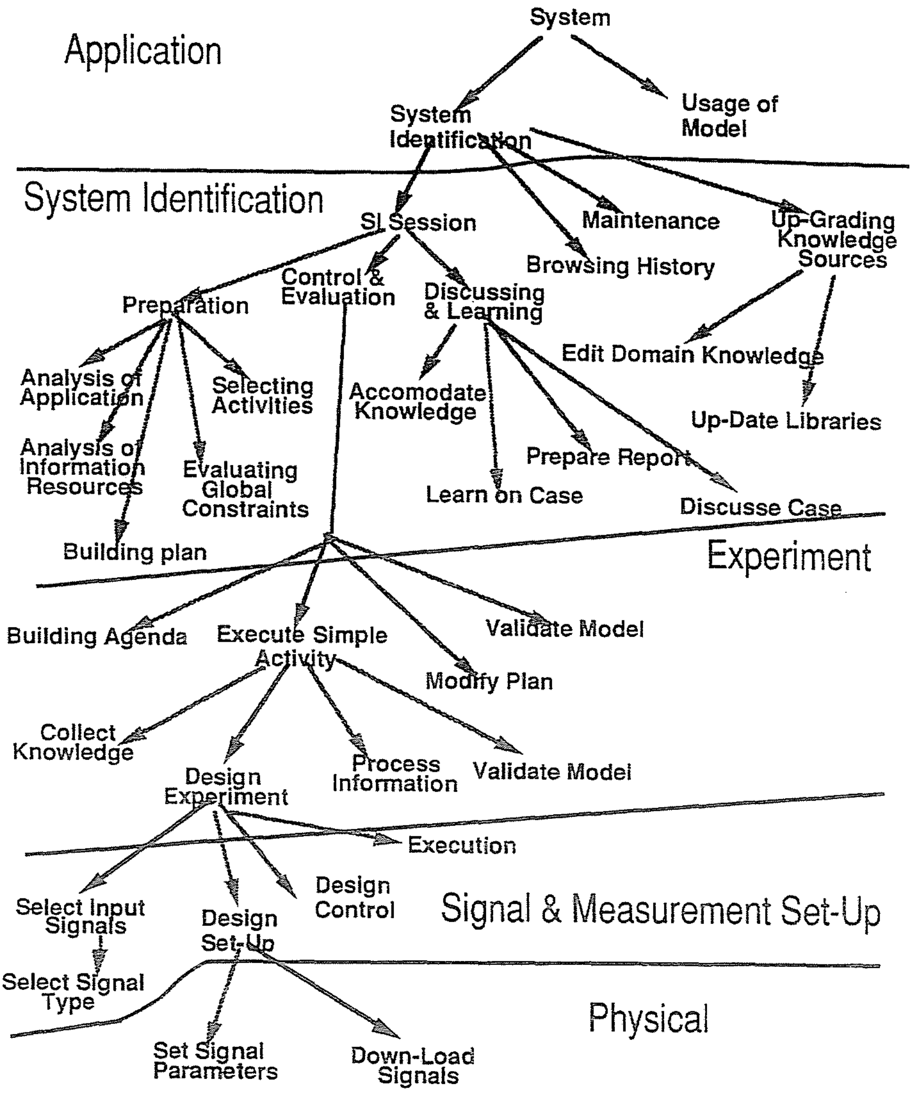

Fig. 5. Fragment of the generic task tree for the SI problem

introduction of the opportunistic control and the heterogeneous knowledge representations and reasoning schemes. Coupling symbolic and numeric processing, or to integrate the system with other system components is also easy to formulate and implement within the task tree (*Fig. 5*).

This so-called '2nd generation' technology was used to develop an experimental knowledge-based system identification platform (LOUAGE et al., 1994b). The developed system fully controlled the connected measurement set-up and used it to organize optimal measurements to obtain good system models with the minimal inference from the user (*Fig. 6*).

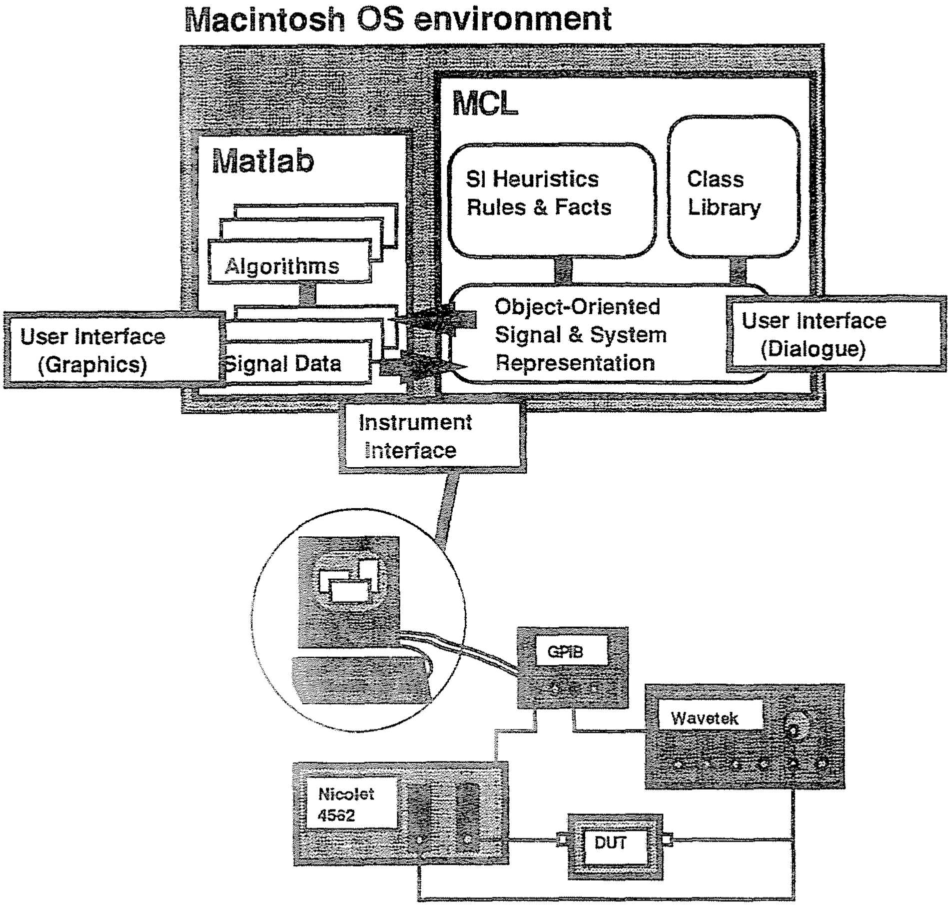

Fig. 6. Intelligent SI platform designed according to the architecture from *Fig. 3*

Recent years have brought the new widening horizons but also the questions. One problem is the future of so-called hybrid information technology in the measurement and within this topic the role of the soft computing tools and other methods related to the imprecise evaluation of the information (MAURIS et al., 1994). Although the advantages of the fuzzy logic are well understood, it has its limitations also (DOBROWIECKI et al., 1995). The primary problem is how different notions of uncertainty merge, especially those related to the finite resolutions of the used models with those stemming from the limited system resources in round-the-clock applications

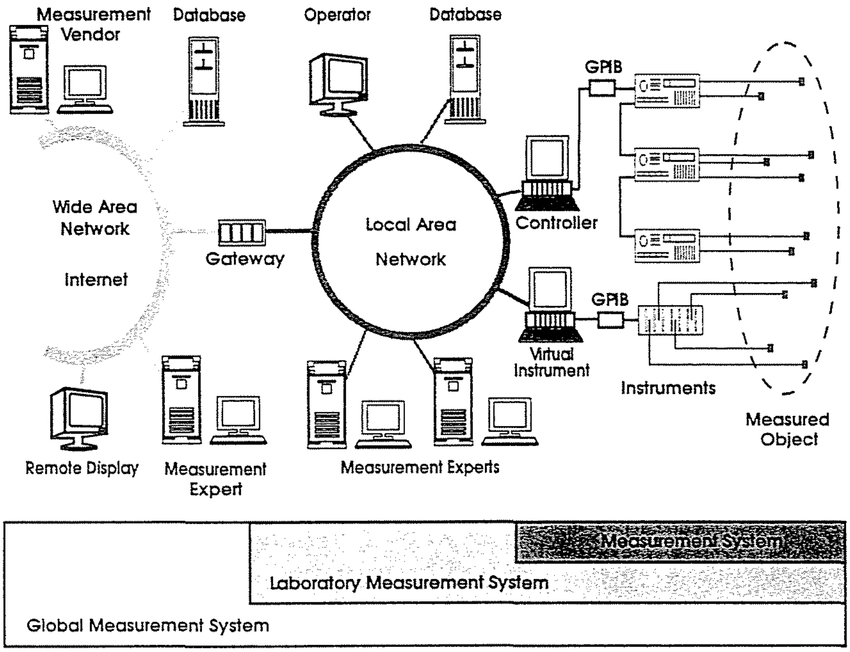

Fig. 7. Coupling measuring systems with global information networks

(VÁRKONYI-KÓCZY et al., 1997).

The notion of uncertainty, coupled with the requirement to control the behavior of the measurement hardware, brings into open the question of qualitative signal and system theory, a reasoning scheme which would yield answers to questions about the signals at various points of the measurement set-up. Quantitative evaluation of the signals is out of question due to the complexity of such computations and to the missing knowledge about the systems signal pass. On the other hand, the knowledge whether the signal at a given point in a given time is 'all-right' is essential to the control of the process. Wrong signal shape can indicate a faulty instrument, erroneous instrument settings, wrongly chosen processing package. Human operators are good at this task, however, they use knowledge difficult to be formalized and utilized within the automated system. Needless to say, research in qualitative signal and system theory has not started yet.

Another question is the marriage of the measuring systems with the global information networks, like Internet, and so-called agent-like system design (GENESERETH et al., 1994). Particularly interesting questions here are how the measurement expertise can be spread and collected and how the traditional architecture of the (distributed) measuring systems could be extended (DOBROWIECKI et al., 1996). The problem is serious because the actual measuring systems reached already that level of complexity in hardware and software, which makes the coupling to the information networks natural (*Fig. 7*). Developing system controllers with agent architecture yields an opportunity for a more intensive expertise retrieval and a (world-wide) distributed measurement design and evaluation of the measurement results.

4. Conclusions

Measurement, as a part of modeling, is that kind of universal problem where the computer system, the analog physical world and the human operators are naturally integrated. Consequently, it makes the automation of any activity related to the measurement very difficult, especially when such issues as complicated measurement task, wide-area distribution, finite system resources and real-time operation regime must be considered. On the other hand, it makes the measurement an excellent benchmark problem for advanced system design, where the new approaches, especially the new artificial intelligence approaches can be verified. Although certain success can be already attributed, fully automated measuring systems or rather intelligent modeling systems are still far ahead.

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