MANAGEMENT OF AGRICULTURAL PRODUCTION SYSTEMS

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ABSTRACT:
This paper addresses the issue of computer-aided decision making for the problem of guiding (e.g. controlling and
monitoring) a beforehand configured agricultural production system. The concerned decisions must enable to reach one
or several objectives at a fixed date, in agreement with the constraints inherent to the physical (i.e. biological)
evolution of the system and those concerning the way to reach the objectives.
Once the problem posed, we suggest, in a first part, a framework structuring the decision process taking place in
the management of production systems. In a second part, several approaches, poorly known but potentially interesting
for the addressed problem, are introduced. These techniques permit to face the exploration of multiple alternatives for
the resolution of planning tasks, and allow modeling and managing systems which are known in a qualitative form
rather than in a quantitative one.

1 INTRODUCTION

We are interested in a production system configured with respect to a desired evolution strategy of the system (e.g. to
increase landed property in the coming years, at the sight of opportunities, without going beyond a certain level of
debt). To configure a system signifies to determine its production means (e.g. the crop machines number, the cultivated
area) in order to realize a certain production (e.g. annual forage quantity).

The problem considered here is the management of configured production system. Having a (minimum) production
objective, for a precise date, the problem is to control the system (acting on it) and monitor it.

The control of the system is done by reasoning actions (e.g. hay cutting, greenhouse heating) that we are going to
apply. The reasoning done, from the past and the current state of the system, bears on an estimation of its future
evolution leading to the desired objective. This evolution is function of :
- the physical behavior of underlying biological sub-system (e.g. plants growth),
- the system environment (e.g. climate, illnesses),
- the actions exerted on it.

The reasoning done is based on various kind of knowledge :
- the previsions on the environment changes,
- the estimation of the plausible effects of the actions,
- the expressed constraints on the way to reach an objective (e.g. avoid heavy jobs during a given period of the year
  because of a lack of available time during this period of time),
- the constraints inherent to the physical system (e.g. do not stress plants inside greenhouses with too important
  variations of temperature).
The reasoning process searches to determine the actions that will guide the evolution of the system. So, it establishes a sequence of interventions based on assumptions. We will call this a plan of actions. During its execution, it is necessary to periodically verify the compatibility between the assumptions and the reality. If what is observed in the real world differs from what was supposed to occur, the plan of actions must be modified (i.e. to adapted to reality). This is what is called execution monitoring.

In the agronomic context, the difficulties in management come from:
- the uncertainty concerning the environment. It is difficult to forecast the climate, the economic evolution of markets, the parasitic attacks, ...
- the difficulty to appreciate the state of the system. An expert is often needed to evaluate the state of a cultivation and diagnose illnesses.
- the variety of information to collect and of needed knowledge in diverse domains such as agronomy, economy, mechanics, ...
- the rapid evolution of technologies, cultivated varieties and ways of conducting the cultivations does not permit a progressive learning (by experience) of the system.
- the disastrous (irreparable) result of certain decisions which could damage the production system (e.g. a pest control not done at the good moment, could definitely endanger the development of the plants).
- the difficulty in the resolution of conflicts when some constraints cannot simultaneously be satisfied. For example, in the cultivation inside greenhouses, the best use of a strong radiation demands an high internal temperature. Jointly, the improvement of a weak vigor requires to reduce the temperature.

Though we also find these difficulties in the industrial context (e.g. parts production in a workshop), the agricultural systems are distinguishable by:
- the preponderant role of the environment, and the inherent uncertainty associated to it (e.g. the growth of the plants is highly dependent on the climate),
- the fact that a part of the production system correspond to a biological reality that is difficult to measure, or even apprehend (e.g. plant vigor),
- the complexity for evaluating the consequences of certain actions. For example, to maintain a high temperature inside a greenhouse will accelerate the development of the plants, but also subsequently, will favor the emergence of diseases.

In order to face the uncertainty, and more generally, the imperfection (imprecision, incompleteness) of available information and knowledge, the management adopted has to be flexible (i.e. tolerating that the reality be different from what has been anticipated) and adaptive (i.e. able to adjust to the reality) to reach the objective. Moreover, to face the difficulty to estimate the consequences of certain actions and therefore the evaluation of the evolution of the system, the chosen management first seeks to avoid disastrous situations (e.g. to regularly do pest spreading, even if it is not always necessary). The preoccupation to use at best the available resources (e.g. the chemicals used for pest controls) is not absent but often considered as secondary: a risked optimization of the profit is not pursued as the primary goal.

Our laboratory has been solicited to realize computer tools facilitating the above mentioned management task for three production systems: tomatoes inside greenhouses, forages in mountainous zone and winter wheat. It appeared suitable to us to elaborate a general analysis of the concerned decision process, and assess the advantages and actual limits of recent approaches. In the next section, a framework structuring the decision process for managing an agricultural
production system is proposed. In the subsequent section, several approaches yet poorly known but potentially interesting for various aspects of management support are introduced. These techniques permit to face the exploration of multiple alternatives for the resolution of planning tasks, and allow modeling and controlling systems which are known in a qualitative form rather than on a quantitative one.

2 ANALYSIS OF DECISION PROCESSES OF MANAGEMENT

The idea is to decompose the problem of managing the system during a certain duration (i.e. to reach an objective for a given date) into a sequence of simpler sub-problems of management during shorter duration. This decomposition of the problem on a time basis implies a multilevel decision structure. Some levels of reasoning (and thus of decision) are according to the considered duration. An other temporal decomposition of decision problems has been proposed by Anthony [Ant 65]. He established a connection between this decomposition and a classification of the decision levels: strategic, tactical and operational. Besides, a hierarchical system with three levels has been introduced by Udink Ten Cate [Udi78], for the cultivation management inside greenhouses. The notion of time is present there without being the essential structuring element.

The identified pertinent durations and their number are function of the desired and feasible fineness of analysis. For example, the shorter duration identified is one day for the cultivation inside greenhouses, where as it is one week for the constitution of forage stocks.

To illustrate our purpose, we consider a decomposition in three levels named: long, medium and short terms. Depending on the problem, a decomposition in two or more than three levels may be appropriated. The figure 1 schematizes the existing links (information flows) between each level.

The hierarchy expresses that a level guides the level below it: it fixes an objective and a set of constraints related to the way to reach this objective. The constraints may be weighted according to the importance given to them (imperative constraints, negotiable constraints).

The pieces of information used by each level (on the state of the system and the environment) can be given by the farmer (observations) or come from others origins (e.g. data banks, sensors). These pieces of information are different from a level to another (e.g. weather statistics for the long term, weather forecasting for the short term). They correspond with different levels of abstraction and are characterized by a higher imprecision (lack of specificity) in the upper levels.

This decomposition seems to be related to a spatial decomposition. The bigger the considered duration, the larger the space to take into account. For a large duration (e.g. six months), the reasoning bears on the cultivation and the farm. For a small duration (e.g. one week), only parcels and plants have to be considered. This decomposition also corresponds to a structuration in sub-problems less and less complex. The simplest ones are the most often resolved. The figure 2 shows the frequency of the resolution of the problems at each level.

Assume that an objective is assigned at the long term level. The unfolding of the management process works as follow. Initially, at the long term level, a plan of action is conceived under the form of a sequence of intermediary sub-
objectives associated to time points. When the time has come, each sub-objective is communicated at the medium term level. In turn, this latter proceeds to a decomposition of the received objective in sub-objectives clearly situated on medium term scale. Each sub-objective is communicated to the short term level which is going to decompose it into executable actions. This unfolding is shown in Figure 2. An impossibility in the effective realization of an objective (or the execution of an action) could bring an ascending reconsideration of the concerned objectives and/or constraints.

For example, for the cultivation inside greenhouses, the long term objective consists in starting to produce tomatoes before a given date and to reach a certain yield. At the beginning of the cultivation, the long term decisions consist of choosing growth objectives expressed under the form of a sequence of values of temperature sum to supply weekly. The medium term is going to define the daily climatic setpoints to maintain during each day of the week, so as to reach the objective at the end of the week. A given day, the short term determines the actions to realize those setpoints. Suppose that it could not, because contrary to the forecast data, the weather is bad and consequently energy consumption required would be superior to an acceptable limit. The short term must notify to the medium term that it cannot realize the objective. The medium term could then adapt, for instance, by releasing the energetic constraint.

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**Figure 1.** Temporal decomposition of the decision process

- Environment information or system state communication
- Decisions communication on the form of an objective and a set of constraints
We are now going to describe more precisely these levels.

**Long term level**

We suppose that a production objective (defined in terms of yield and quality) to reach at a precise date, together with the constraints concerning the way to reach this objective are given. For example avoid scheduling jobs during a particular period in which it is necessary to harvest an other cultivation.

The available data on the evolution of the environment are very uncertain and imprecise (e.g. weather forecasting is poorly reliable or lack specificity on the considered period) and the state of the system is globally apprehended (e.g. productive quality of the parcels). Relevant knowledge concerns very different subjects: general characteristics of production system (e.g. thermic quality of greenhouses), cultivation techniques, ...

The problem to solve is one of planning. Decisions to be taken aim at defining an anticipated procedure: determining intermediate objectives (reference states) to be reached at particular dates (reference dates). It could be named a plan or a program. It is actually a partial plan (incomplete), flexible enough for matching (as much as possible) with real situations. Since the execution world is unknown beforehand, the plan of actions cannot be very precise. It is rather a behavior line adopted according to the assumptions done on important parameters (e.g. climate). In the case of the constitution of forage stocks, the plan is described under the form of reference states (end of silage at the middle of June, end of the first mowing at the beginning of September) and of technical pathways associated to each parcel (do a silage and next a mowing).

At reference dates, a monitoring is done to evaluate the current situation with regard to a sought reference state, and to adapt the plan if necessary. If the reference state is reached, the plan is pursued. If not, it is necessary to do a diagnosis of the causes. Once these causes are determined, the plan must be modified in order to take into account the unanticipated context. Since some problems occur rather frequently, the necessary fits to adjust to them can be prepared in advance and associated to the plan. We call them adaptation rules (e.g. if the silage is not finished at the middle of June due to bad weather then ...). In the worst case, it is no longer possible to reach the objective from the current
situation. The best is then to notify it to the decision maker (e.g. the farmer) which has fixed the long term objective.

**Medium term level**
The objective to reach here (e.g. for the constitution of forage stocks, to obtain a given yield of silage using the given anticipated technical pathways; for the cultivation inside greenhouses, supply a sum of temperature) is defined by the upper level as are the constraints to satisfy (e.g. a correct and simultaneous development of the different states of plants: flower, fruit).

The data concerning the environment are more precise and often more certain than at the long term level (e.g. weather forecasting for the week). Some pieces of information about the state of the system are hardly measurable (plant health, leaves appearance) but can be assessed by a human observer. The phenomena intervening at this level (e.g. photosynthesis, energetic balance-sheet of greenhouses) are relatively well known and allow better anticipation of the evolution of the system.

The reasoning process aims at establishing a more specific plan than previously (in less general terms). For example, the problem consists in determining a partial schedule of the parcels to ensile or the daily climatic setpoints to maintain inside the greenhouse. After inventory of intervening constraints, they are aggregated. Taking simultaneously several constraints into account generally leads to the problems of conflicts resolution and combination of convergent constraints. There is a conflict, when, at least, two constraints cannot simultaneously be satisfied. Two constraints are convergent when they suggest similar actions. Conflict resolution is done by ignoring some negotiable constraints. If the conflict persists after having ignored all the negotiable constraints, it means that there is no solution to the stated problem. The medium term then has to inform the long term which must decide on an appropriate adaptation. For example, change some constraints or convert initially imperative constraints into negotiable ones.

As previously, the execution of the plan has to be monitored.

**Short term level**
The goal is to reach the objective given by the previous level (e.g. to maintain given climatic setpoints inside the greenhouse, to ensile a set of parcels) according to supplied constraints (e.g. begin with the bigger parcels).

The available data are rather reliable, the involved knowledge is simpler (more technical).

At this level, the reasoning process does not require to consider multiple alternatives based on assumptions. Conditional pieces of knowledge directly provide command decisions specifying executable actions (e.g. if a strong wind is blowing do not open airing panels, if the humidity rate is higher than a threshold S then ventilate).

As at the other level, an execution monitoring must be done. The necessary adaptation are quite simple and could be estimated in advance under the form of if-then rules.

The control theory techniques and the available tools on the market have already given satisfactory results but they are not applicable in all cases.

The decision process that we have described is consistent with the modern vision of it: distributed in time, sequential,
based on a decision maker model with admitted bounds of rationality, taking into account multiple criteria, seeking the first satisfactory solution rather than the best solution [Sim82]. On the basis of these principles, Sebille (see for instance [Seb88]) has proposed a framework (called 'modèle général') suited to the decision making process of farmer. Our approach is conceptually close to this model but more oriented toward a computer implementation.

3 SOME INTERESTING TECHNIQUES FOR THE MANAGEMENT

The full management of agricultural production systems has not received a satisfactory computational solution yet because the available tools were not suitable for a global enough approach and for facing the characteristic difficulties of the problem (see introduction). In the sequel, we present some relatively recent techniques, still poorly known but very relevant to some of the important problems we have point out. However one should not think that everything is going to be solved by their immediate and direct applications : we have no pretension of providing the solution. All we want to do is to focus on these techniques in order to show their power, scope and limits.

3.1 PLANNING

Planning means here the process of reasoning about future events, to select, or at least verify, the existence of a reasonable succession of choices of actions to achieve an objective. Therefore, a plan is a description of a set of actions organized according to a temporal structure, and planning is a construction process of plausible futures, satisfying given constraints.

At the center of this general problem, lies temporal reasoning as well as reasoning about actions, about intentions of others involved agents and reasoning from incomplete knowledge. In order to satisfy one or several objectives, a planner often has to solve combinatorial explosion problems. Several difficulties can complicate the task. The time required to obtain a solution may not be sufficient. Sometimes, the necessity to act does not leave any time to make predictions. One must then make use of and rely on rational assumptions. An other difficulty is that some pieces of information for a solution may not be accessible and may vary dynamically ; thus preventing an execution of the plan as expected. In such a case, complementary information have to be acquired during planning and execution. In many case, the planner must accommodate conflicting objectives.

Plan generation and scheduling

In the Artificial Intelligence (AI) literature, two types of problems that aim at establishing a sequence of actions to reach an objective, seem to be distinguished : planning (i.e. plan generation) and scheduling. In the first problem, a reasoning is needed to decide whether to act and how (which actions to choose, in what order) ; a central activity is then to determine how a given situation is affected by a new event (an action for example). In the second problem (scheduling), the goal is to produce the best timing for the actions ; the decision to act is no longer to be taken and the set of actions to perform is already partially determined by the available resources and the characteristics of the manufacturing process. The problem consists in satisfying a set of constraints [Wil88] without having explicitly to reason about the changes that an action could cause in the environment.

Strictly speaking, outside of the AI context, scheduling may be seen as a specific, but nevertheless complex sub-
problem of planning. Specific, because typically a scheduling task is done in a strongly structured world. For example, for a job-shop scheduling, little preconceived plans are available beforehand. They specify machining operations, their execution order and which machines have to be used. The complexity generally comes from a situation where several agents interact and for which a great number of potential solutions are possible. Essentially, in a scheduling problem we want to find an optimal (or modestly a good enough) solution by playing on the temporal constraints (due time, slack) and those bearing on the resources (limitation of availability). This notion of optimization, central in a scheduling task is absent (secondary or not relevant) in the resolution of an AI planning problem where what is important is to structure (by reasoning on the effects of actions) a sequence of actions satisfying the objectives.

In practice, scheduling mainly concerns technical and industrial processes. For instance, in order to reduce production time and to adapt to fluctuations in the demand, manufacturers have to solve a scheduling problem that can be defined as follow. Given:

- some means of production, capital goods and functioning constraints,
- an objective of production defined in terms of yield and constraints to fulfill (quality, deadlines),
determine the order in which the required operations must be realized with the available means of production in order to reach the objective. Usually the resolution of scheduling problems is dealt with in an Operations Research (OR) setting. However, this type of approach suffers from its rigidity (difficulty in formulating an objective function to be optimized, difficulty to take into account empirical and poorly structured knowledge although high valuable). In the past ten years, some have tried to reconsider the problem in a purely AI setting [Dee86] [Fox82] or by using a combination of AI and OR techniques [Bed87]. The latter seems promising to accommodate global (logical) constraints on chronology (related to availability of resources, duration of tasks, ...) with pragmatic methodological (empirical) knowledge.

Plan generation is the construction of a sequence of actions that satisfies the specified goals in agreement with the constraints of the universe in which these actions are to be executed. A plan generator reasons on the changes caused by the actions. A planning problem is specified in terms of the following elements: a description of the initial state of the environment, a collection of actions for modifying the environment, a body of knowledge clarifying the conditions under which each action can be performed, and a set of goals corresponding to a final date. Commonly, a plan is a linear (totally ordered) sequence of actions. However, more complex constructions, based on a more sophisticated treatment of time, enable to conceive plans in which actions can be executed in parallel.

In AI, planning essentially means plan generation. However, it is important to associate with it the problem known as execution monitoring (constructed by the plan generator) of the plan. Indeed, generation and execution are strongly dependent: an execution failure may require the generation of a new plan.

Execution monitoring
Basic planners build complete plans of primitive (executable) actions before they start to execute them. At execution time, each action is accomplished by tools and machines. For many reasons, the execution of an action may fail (e.g. breakdown of a machine, occurrence of unexpected events). In order to insure that desired effects effectively occur, it is necessary to use a separate system, controlling the execution and deciding what to do when something is wrong.

More specifically the execution monitoring must detect problems as early as possible. These problems do not necessarily become apparent through immediate effects: an intermediate goal that cannot be reached. For instance, such
a problem can be due to an early termination of the validity of a condition that was supposed to be true for a longer period by the planner. Besides being subject to failure, the devices used to execute the actions are unpredictable on several occasions (e.g. a robot that is asked to take object A, may take object B instead). The reality, in which the plan generator has been made, may have changed unexpectedly. Moreover, the causality in the considered universe may be incompletely or erroneously known.

What can be done to recover from a situation where a problem has been detected? There are several possibilities depending on the case:

- generate a completely new plan from the current state of the universe, but this solution is often unacceptable (the required time may not be available),
- generate a little plan to transform the current state into a situation where the current plan could be carry out (this is appropriate if what has been performed so far makes the goal closer),
- if available use reactive plans (precompiled conditional plans).

Among specific works done in execution monitoring and recovery from error are those on triangular tables that came out of the STRIPS [Fik71] project. A triangular table is a data structure that represents a plan, the preconditions of each action and the link to the source of their satisfaction (either the initial state or a state resulting from the execution of an action). This structure make it possible, in some cases, to use part of the initial plan when the context of execution is different from the expected one.

In spite of the STRIPS example, AI research in the planning domain has not given sufficient attention to the execution monitoring problem. In the last five years, things have changed and this problem has become a major subject in the field. In particular, progresses have being made in the integration of planning and execution such that the acquisition of knowledge during execution is included in the plan (the data collected are then used appropriately to guide the execution).

**Current research in planning**

From a practical point of view the interesting applications of planning are mainly in dynamic, incompletely known and multiagent worlds. The planner built, until the early eighties, were unable to deal with such situations. To make it possible, research works have been undertaken around the themes: multiagent planning [Fer88], reactive planning [Geo87], and approximate temporal reasoning.

a) **multiagent planning**

The goal is here to simulate a complex world where several relatively autonomous agents cooperate or compete, making a dynamic process. Each agent can elaborate plans taking into account its own objectives as well as the intentions and believes of other agents. The communications with other agents are considered at the same level as the actions. The hypotheses made for single-agent planning are here inappropriate. In particular, one cannot consider each action as a transition between states because the effect of an action depends on everything that can occur during the action and, in particular, on the actions that may or must occur simultaneously.

More powerful capabilities are required for representing and reasoning about sequences of states (which are called chronicles: possible histories of the world). Goals are more sophisticated: they may have to be satisfied according to given time constraints and they may interact heavily (conflicting goals for an agent or goals creating conflicts among agents). Ignorance, indecision, indetermination of an agent in a situation are important concepts that must be
represented. As far as time management is concerned, it is almost compulsory to deal with continuity, simultaneity (e.g. for representing coordinated actions of two agents) and synchronization of actions of several agents.

A planner in a multiagent world requires a reasoning module supervising the different agents in order to share resources and decide how to schedule the actions ultimately. In a situation of choice, this module must analyze the different alternatives in terms of utility (relative benefit from an action) and uncertainty (to what extent an action will be executable and will give the expected results). With competing agents, the decision process may be guided by principles inspired by game theory. In a situation of cooperation among the agents, the decision can be taken on consensus criteria, based on group decision techniques (some operations research approaches, e.g. voting procedures, seems very relevant here).

To summarize, multiagent planning is more complicated than classical planning (which is not trivial at all). Besides the central role of action, other important concepts such as reaction, interaction, communication are involved in the reasoning process. Several approaches have been explored but existing implementations are rare and limited in power and scope.

b) Reactive planning

A dynamic world cannot be modeled completely. The execution must involve a reactive reasoning [Geo87] in order to permit adaptation to changing environment. A precise plan would be inappropriate because evolution is not always predictable and too many alternatives would have to be considered. Plan generation and execution must be tightly linked in a system monitoring effects of actions, unexpected events and any new information that can contribute to a validation, a refinement or reconsideration of the plan or goals. Reactive planning is confronted to the problem of real time response because time required for a plan generation process is not always available. The reaction of a system working in a dynamic world must preferably rely on perception rather than prediction (obviously limited).

Planning suitable to hardly predictable situations must be more robust than classical planning which takes place in a quasi-static world. Plans must be represented in a highly conditional way, such that tests and associated responses can be integrated. Information gathering must be planned as any other action. The elaborated plan can only be partial because its complete determination depends on information obtained during execution. The real time planning (to be done at execution time) must be reduced as much as possible. This may be realized by extrapolation or by forcing the problem to fit a situation where no prediction is needed and feedback adjustment is possible and sufficient (as in control theory).

Finally, in order to allow a plan to react appropriately to unanticipated situation, the intention and the goals may have to be reconsidered in the light of new data.

Current works in reactive planning are oriented toward the construction of systems capable of anticipating, as much as possible, the execution environment [Agr87]. Some techniques have been developed for compiling procedural knowledge about the way to satisfy a goal, for using wisely the possibilities of data collecting, for resolving conflicts in real time and for integrating specialized planners (e.g. to find trajectories) in general planner. The main domain of experimentation concerns the problem of robot navigation. The current systems do not address the planning problem in its globality. In particular, they are unable to perform reasoning on priorities of goals (in which order should they be considered), on whether the plan can be modified and how (deliberation time needed to build a new plan must first be
evaluated) and on the decision to abandon a plan.

c) Imprecision and uncertainty concerning time

Dealing with time can hardly be done without taking into consideration the imprecision and uncertainty pervading temporal information. For instance, although a robot is able to read time exactly, the occurrence and consequences of an event affecting it may not be known precisely [Dub87] (e.g. the repairer will come at around noon and then the pump will be reactivated and the machine will work 45 minutes later). Uncertainty may come from a lack of information about the initial state, about the effect of some actions (non-determinism), about the intentions and actions of other agents if any. Another important source of uncertainty is related to the prediction of a fact true at some time but whose persistence vanishes after a while (e.g. if one forgets a wallet on the table in a restaurant, the fact “the wallet is on the table” does not remain true for ever). By default, current planners use (implicitly) a rule of persistence which tells that a fact remains true until it is explicitly stated that it has turned false. The problem with this rule is that one must be able to predict the case when the fact becomes false; this is not always possible (e.g. one cannot predict what may cause the disappearance of the wallet and when). In this case, the notion of persistence is more appropriately represented by a numerical uncertainty measure (probability, possibility). A robust planning system must be equipped with capabilities to reason in uncertain and imprecise environments. Few publications [Dea88] deal with this subject but the concern is often expressed in recent works.

So far few applications of AI-based planning [Wil88] to real world problems have been realized. It is worth mentioning that until the advent of AI, planning tasks had never been the object of any automation attempt, except those of scheduling in the operations research context. The explanation of the mild success of AI approaches to the planning problem may be that plan generators (which are very sophisticated inference engines) are efficient enough and address too simple situations that do not fit the complexity of the real world. In particular, they have been conceived to operate in relatively static environments. Consequently, current planners are poorly suited to a use in a dynamic setting where time to deliberate and act is limited. But that is precisely where planner may be useful. Moreover plan generator for static environments have been programmed with generality in mind and, thus, suffer from inefficiency. For specific tasks (e.g. path planning) there are efficient algorithms. Nevertheless, recent progress in the field offer great potentialities for the management of agricultural production systems.

3.2 QUALITATIVE KNOWLEDGE

Qualitative causal reasoning on continuous systems

In order to deal with the dynamic behavior of complex system on an interval of time, it is useful to have a model (a representation) of it that is an abstraction or simplification of the reality. The main goal is to reproduce (simulate) the global behavior of the real system (i.e. its evolution under some conditions). The design of a model is determined by the system to be represented and by the questions one wants to ask. The difficulty in designing a model stems from the types of knowledge to take into account (e.g. spatial, temporal, imprecise, incomplete).

The classical and well spread approach represents mathematically (by use of differential equations) the dynamic behavior of the system. It is particularly appropriate when the system to be modeled is described through objects that change continuously and in a completely known way (or assumed so). Since less than ten years, the symbolic simulation of continuous systems has been created: this is the so-called qualitative simulation [Kui86] developed by artificial
intelligence scientists. Its motivations and differences with numerical approaches are briefly presented in what follows. Everybody’s experience shows that, for many tasks implying a reasoning process on the evolution of a system, the common sense reasoning is sufficient for solving the considered problem. In this case, the natural method that bears on a qualitative apprehension of the reality is very efficient and often is proving more appropriate. Actually, representing mathematically and accurately all what is necessary to a given task may be very complex or even impossible. The main motivation behind qualitative reasoning research comes from this fact. The advantage of the qualitative approach is that it can work with partial, imprecise (coarse) knowledge of the system and of the particular situation considered. On the opposite, numerical simulations demand very precise details (for either representing the system or describing an initial state) that may not be available or necessary from a theoretical point of view.

The mathematical approach is hard to satisfy in terms of required information but for all that it cannot capture some important aspects of the behavior of the system as the appearance and disappearance of objects composing the system. In addition, it must be pointed out that a mathematical representation of a system does not help much to understand its functioning because important concepts are then embedded in numerical variables and differential equations, the resolution of which is done through an opaque process. In a qualitative reasoning, the concepts appear in a symbolic form that is simpler and more concrete.

Finally, numerical simulations focus on finding the precise solution associated with a well-defined initial situation. The simulations based on qualitative reasoning do not have to confine to single projections: the different alternatives are produced, reflecting the limits of available knowledge.

The qualitative description of a mechanism is also done via a collection of state variables and a set of constraints that the variables must satisfy. Some researchers (for instance [Dek84], [For84]) provides some methods to directly derive constraints from a higher level (more abstract) description of the structure of the system. Although varying continuously a variable take values on a discrete and finite set of symbols denoting landmark values (at a given time, a variable is then equal to such a landmark or between two consecutive landmarks). In addition to its value, a variable is described by the direction of change (the qualitative derivative). The dynamic behavior of the system is represented by a sequence of qualitative states of the variables (a state is given by a pair ‘value-tendency’ for each variable). Such a sequence is built from an initial state by a qualitative simulation which is a temporal symbolic reasoning on the ways a variable may change. Qualitative simulation departs from numerical simulation on at least two aspects:
- time is decomposed according to the occurrence of interesting events rather than a fixed step,
- the limited precision of qualitative representation make it necessary to consider several alternatives for possible futures.

The term qualitative physics denotes qualitative reasoning on a physical system [Dek84]. Qualitative physics produces a qualitative account of the behavior of the system and a causal explanation of this behavior in terms of a qualitative description of the initial situation.

The figure 3 summarizes the analogy and the contrast between the mathematical and qualitative approaches. Stating from an initial physical state, each approach models in its own way the situation and the physical reality of the system. The mathematical approach essentially relies on normal differential equations.
In qualitative physics, a set of constraints is used to explicit how the parts\(^1\) of a system are organized in a coherent whole. Such a structural description, expressed in terms of state variables and constraints bearing on them, can be seen as a qualitative abstraction of differential equations, sometimes called qualitative differential equations. A continuous state variable takes value in a discrete and finite universe (possibly partially ordered) representing critical or landmark values of the quantity space of the variable. A qualitative state is described by a pair (value-tendency) where value is either a landmark or an interval bounded by landmarks and tendency is one of increasing, decreasing, steady. The properties of continuity can be translated into a finite set of relations on a finite set of symbols.

On Figure 3, one can see that the numerical approach requires an interpretation process (poorly automated so far) of the numerical outputs. Indeed a standard numerical simulation provides a list of state vector, each vector describing the state of the system at a given time point. In qualitative reasoning, the behavior of the system is expressed analogously by a sequence of qualitative states of the variables. Some qualitative states describe episodes: they concern temporal intervals during which the variable have had a specific evolution.

Because a qualitative description of an initial situation and of the physical reality of the system is often incomplete, it is likely that the behavior induced by qualitative reasoning is not unique. The different possible alternatives are produced by the resolution mechanism. This capability is very convenient to discover unthought pathological situations. However, current techniques of qualitative simulation are too elementary and may produce solutions corresponding to behaviors that are physically impossible.

![Diagram](image)

**Figure 3. Analysis of a physical system: numerical and qualitative approaches**

Practically, a qualitative reasoning on the principles underlying the evolution of a system may be used to explain observations (e.g. failures) in a causal manner and predict future events (simulation). Besides the 'why' and 'what's happen if' questions, qualitative reasoning is interesting to address issues such as: 'what is the role of the system' (function extraction), 'why is it not working' (diagnosis), 'what may cause what is observed' (theory formation), 'what is the effect of a given change' (comparative analysis), 'how to correct a malfunction', 'how to conceive the system in order to make it fit some specifications' (design).

\(^1\) Several languages for describing a system have been studied in qualitative reasoning research. They exploit different abstractions of the reality: the parts of a system are, for instance, physical components [Dek84] or processes [For84].
The potential applications of qualitative reasoning are essentially in diagnosis, design and control of physical systems. Presently existing implementations are small scale research tools. Many unsolved problems remain. In particular, bridging the gap between qualitative and quantitative is still to be done : how to use data coming from sensors in a system described qualitatively. Moreover, it is necessary in practice to be able to use cooperatively qualitative knowledge with numerical models when these are available because, often, some parts of the system under consideration are representable in a precise mathematical way, whereas others are only understood qualitatively. Numerical precision is compulsory for some problems. Qualitative reasoning as done by current softwares is too simplistic because they rely on too poor information ; numerical information that could help in getting rid of some ambiguities cannot be exploited by these programs. An important subject of current research aims at adding redundant, semi-quantitative information to qualitative models (e.g. representing orders of magnitudes of the values of the variables [Rai86]) such that the generation of impossible behavior can be filtered more severely.

Despite its limits that we have pointed out, the increase in the number of publications and the creation (in universities, by companies in the United States, Japan and Europe) of research groups around the theme 'qualitative reasoning' shows a significant vitality and a potentiality that should lead to non-trivial applications within ten years. The nature of agricultural systems, the kind of information involved, the problems and expected solutions indicate that qualitative reasoning is worth considering for the future generation of softwares for managing production systems.

**Fuzzy controllers**

Control tasks (encountered at the short term level of our analysis) aims at linking command variables of a process to variables that can be observed as output of the system. Two approaches are possible to face such tasks. The first one is based on a mathematical model of the process (classical control theory, e.g. PID control). The second approach consists in modeling the behavior of an expert able to control the system (control based on empirical rules of know-how).

Human operators are sometimes able to control processes with better performance than any other technique. In this case, the inappropriateness of modern methods is due to either a poor understanding of the process, making difficult (or impossible) the construction of satisfactory mathematical models or the impossibility to measure some of the observed variables. In such a context, a human expert can still do the job. Automation control task for such processes is valuable because it permits an optimization by using knowledge of the best experts and avoiding variations in quality and inconsistencies that may occur when switching from one operator to the other. Fuzzy control techniques have been developed in this spirit.

The know-how of an operator on the way to control a process is naturally available under the form of rules as for instance : "if the temperature is high and has increased rapidly then, reduce significantly the injection of oxygen". This kind of rule links observable outputs described qualitatively to qualitative pieces of advice on command variables. Each rule is stated with respect to a setpoint (e.g. the temperature at which the system must be maintained) and is based on an output variable and its variation as for the PD type controllers. The specificity of the fuzzy controller approach stems from its utilization of linguistic terms such as 'high', 'rapidly', 'significantly' that are meaningful for an experienced operator but rather difficult to communicate to a computer.

The fuzzy control techniques represents knowledge by use of a collection of rules similar to the above stated one but using a more restricted vocabulary (about ten fuzzy linguistic terms). For a single-input single-output process, the rules
are for instance:

"If ε is PS and δε is PB then δc is NM", "If ϵ is ZO and δε is ZO then δc is ZO"

where ε is the error with respect to the setpoint, δε is the variation of the error at a given time point, δc is the variation of the output variable. The linguistic terms PS ("Positive Small"), PB ("Positive Big"), NM ("Negative Medium") and ZO ("Zero") are represented (see Figure 4) by fuzzy sets on the [-1, 1] scale, that is to say subsets of [-1, 1] having ill-defined boundaries. A fuzzy set is represented by a membership function μ from the referential set (here [-1, 1]) to [0, 1], μ(u) = 1 means that u belongs to the considered fuzzy set, μ(u) = 0 signifies that it does not belong to it and 0 < μ(u) < 1 expresses a partial membership. For instance, the set of tall heights of human is a fuzzy set because some heights belong more or less to the set due to the vagueness of the predicate 'tall'.

Figure 4 - Membership functions of some linguistic terms

The typical inference mechanism used in fuzzy controllers is much simpler than inference engines of expert systems: in most cases there is no chaining of rules. Fuzzy controllers work as follow:

- In the first phase, the values observed for output variables (that can be assessed imprecisely when measurement is difficult) are compared to the corresponding values in the condition part of each rule. A matching index is computed to evaluate to what extent the conditions of the rule are satisfied by the observed data. Several rules may return a non-zero index. In other words, each rule has a region of influence that overlap with the one of other rules; fuzzy controller rules are not mutually exclusive and more than one rule may contribute to a particular command decision.

- In the second phase, the conclusions of rules having a non-zero matching index are combined (usually a kind of truncated union of fuzzy sets is performed) and the command decision is determined by taking a particular point of the resulting fuzzy set (several choices are possible depending on the application).

The acquisition of control rules can be done either directly by questioning a human operator or indirectly by extracting them from traces of cases. The number of variables to take into account is not limited.

The main advantage of fuzzy controllers is to provide a flexible means of interfacing numerical information (i.e. the measured values and command decision) with qualitative and symbolic knowledge: the rules using linguistic terms). The fuzzy control technique is basically an interpolation method that preserves continuity and avoids threshold problems. It is interesting to note that a small set of rules is sufficient to describe a robust, flexible and efficient control algorithm.

Although the fuzzy control theory has its roots in England (Mamdani's research [Mam75] at Queen Mary College) and the first large scale application is Danish (F.L. Smith & Co system in 1980 for controlling energetic input in a cement kiln) the diffusion and massive utilization of the approach is due to Japanese companies [Sug85]. Now there are many
practical realizations in the industrial world. Let us mention, for instance, Hitachi’s system for controlling the stopping of an underground train in a way compatible with criteria of comfort, security and precision that are expressed linguistically. Another example is the controller made by Fuji Electric that aims at regulating the quantity of chemicals necessary to purify water of rivers depending on its turbidity, alkalinity and other factors. As far as we known, very few applications in agriculture exist today but the fuzzy control methodology seems appropriate for production processes in the food industry.

CONCLUSION

The computer technology bring decision support to the farmers or agriculture council organisms in several ways:
- to access to available information at various sources (e.g. weather forecasting, economic anticipations),
- to analyze accumulated data (e.g. statistics),
- to estimate the current state of the system (e.g. expert systems for diagnosis in phytopathology [And87]),
- to plan interventions (e.g. harvest date, chemical spreading date),
- to understand and model the underlying biological sub-system,
- to evaluate of the consequences of given constraints, in relation with the satisfaction of an objective.

The management of agricultural production systems potentially needs these different capabilities. In this paper, we have particularly stressed on the last three. They are much more difficult to implement and almost absent in the computer assisted decision making systems existing in the agricultural world.

Generally, the decision systems for helping in the management of production systems are mainly thought and principally realized in the following four frameworks:
- decision analysis which combines some aspects of the systems analysis and of the statistical decision theory. It requires to represent the problem in a highly aggregated form (i.e. decision tree).
- operational research, optimization and mathematical modeling for approaching some scheduling problems and realizing simulations.
- control theory which addresses the problems of low level control.
- Artificial Intelligence (AI) which, by the way of expert systems or knowledge-based systems (for diagnosis, conception, planning for example), has brought a new impulse during the last fifteen years.

It is often acknowledged that AI approaches facilitate the use of poorly defined (empirical) knowledge which is difficult to represent in others approaches; this indirectly brings more flexibility and robustness. The different approaches have their own specificities: they are well adapted for some problems and particular situations, and are inappropriate in other cases. Only one of them could not solve completely the problem; the initial objectives of each approach are different.

Staying very general, note that the mathematical approach seeks precision and completeness, whereas an AI system has to be sufficiently robust to face some limitations in time and information (for example, to work with erroneous data). In a same application, several approaches may then have to cohabit. Their integration in a big software does not seem problematic as long as they are used separately and independently. It seems much more complex to combine them in order to make them interact and cooperate (the information required for an approach may be of different nature than the ones used by other ones).
The diversity of the approaches covers a spectrum of applications going from known, deterministic systems associated to quick and frequent execution processes (for which the numerical approaches are naturally appropriated, especially in control theory) to incompletely known systems, pervaded by uncertainty, where the nature of the problem requires an exploration of multiple alternatives. Between these two, lie systems having a structure known to some extent (qualitatively). The AI research done on qualitative reasoning concerns this type of systems.

Studies and research in control theory, operational research, decision analysis and artificial intelligence have been done for the management of production systems. The more convincing results concern the automation of the low level control. The current development of computer support for the higher levels are oriented toward a semi-automatic approach. The human operator has to be integrated in the decision process: so it is necessary to conceive support systems able to 'understand' the actions of the operator and understandable by the operator [Boy88]. On this point of view, the AI techniques has an important role to play. As we have said, the road is still to be constructed, but right now we think that a part of the technology is ready for undertaking applications in the agricultural domain.

BIBLIOGRAPHY


