# QUALITATIVE PHYSICS APPLIED TO A DEPROPANIZER IN PROCESS CONTROL

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## 1. Introduction

The debate about deep/shallow knowledge has been identified in the AI community [HAR82]. In the context of process control, cognitive ergonomists draw a similar distinction. Operator's activity can be classified in three layers [RAS83] : skill-based, rule-based and knowledge-based behaviours. The knowledge-based paradigm implies a deep understanding of how physical systems work [JAK86].

Recently, Qualitative Physics (thereafter called QP) theories [DeK84] [FOR84] [KUI84] have endeavoured to simulate human understanding and to produce causal accounts of many physical systems behaviours.

The examples given in QP literature are often "toy problems": the devices are simple and well understood, e.g. a bath-tub or a coffee machine. Using the QP representation for a real world problem is a challenge:

• An important problem with QP is indeed to formulate a set of qualitative relations involving an appropriate set of parameters of the device to be represented. When the device-topology approach of DeKleer seems partly inapplicable, and when the physical equations are unavailable or unusable, *knowledge elicitation* **becomes a key issue.**

• Another unsolved problem with QP is *to generate from raw data (especially numerical data taken across time) a qualitative understanding of how a physical system behaves*, in order to disclose internal evolutions.

This paper presents how QP knowledge representation can provide a helpful model of an industrial process. Section 2 describes this process: a depropanizer in a refinery, and the operator control activity. In section 3, we explain why and how we built this QP model on the basis of an existing pedagogical model. Section 4 is concerned with using the QP model for both prevision and diagnosis, two fundamental activities in process monitoring.

## 2. Study of a Real Case

### The depropanizer

Depropanization (fig. 1) is a continuous distillation process. A flow (F1) of C3/C4 mixture with an unknown quality (A1) enters the distillation tower where the pressure (P1) conditions produces a flash (split between liquid and vapor phases). Heat (Qr) is provided at the bottom of the column by a reboiler and extracted at its top by a condenser (Qc). Bottom product (flow F4) and head product (flow F5) must meet quality criteria (A4 A5). The liquid/vapor equilibria on the tower trays are modulated by the reflux (F2) which regulates the "sensitive tray" temperature (T3).

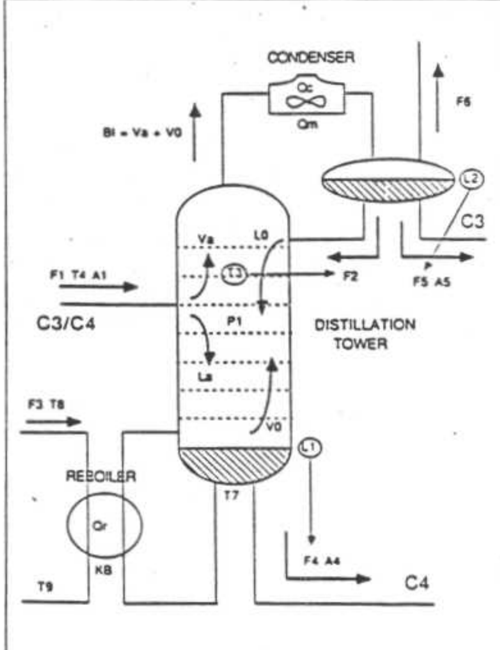


Figure 1 : the depropanization process

Data on the depropanizer are obtained through a set of sensors (called the *Sensors Set*). Qualities are known with such a delay that they must be considered unavailable for short-term analysis. Other parameters such as the condensing power (Qm) or the reboiler efficiency factor (KB) are unknown.

There is a set of possible *causes* (called the *Perturbations Set*) of behaviour changes. Some of these parameters can be controlled by valves (e.g. operator's action on the input flow in the reboiler F3), others cannot (e.g. a change of temperature T4 in the input mixture). It must be stressed that some parameters are not even measured, e.g. A1 or KB. So their variations are difficult to diagnose.

These perturbations do not lead monotonically from an initial state of the tower in stable equilibrium to a final stable state: According to the experts, these transitory variations are difficult to analyse (delays in disturbance propagation and controller responses).

We had the opportunity to use a numerical simulator, (designed and used for training purposes), as a valid approximation of reality. The simulation is dynamic and not of a black-box type. Hence careful experiments have been possible by monitoring the evolution of all physical parameters of the process, measured or not.

**Operators activity**

Operators are required to control this type of process which cannot be fully automated.

This control activity consists of reading and interpreting sensors in order to globally understand a given situation: what is happening, what are the causes of the disturbance and what are the proper actions.

This is why operators are taught the physical phenomena underlying the distillation process. It helps them to justify the rules which can be applied in well known situations, and also to cope with more difficult ones.

This teaching is essentially **qualitative.**

The following explanation is a description of the depropanizer disturbed by an increasing temperature in the reboiler. The reader is not expected to understand the details of this explanation but should just get a feel for the style of reasoning involved (see fig. 1):

*When the input temperature in the reboiler T8 increases, the amount of energy transfered to the bottom of the column Qr increases. The pressure in the tower P1 staying steady, the reboiling flow VO increases. There is no change in the flash zone, so the vaporized part of the feed Va stays steady and the vapor in the top of the column BI increases. That should lead to an increase of the "sensitive tray" temperature T3 which is controlled, so the reflux F2 increases ...*

The attempt to formalize this type of reasoning led us to use QP to modelize the depropanizer.

## 3. Knowledge elicitation and modelization

The QP model developped is made of forty constraints and fifty parameters. We used Kuipers formalism to represent the qualitative relations between parameters [KUI84] [GAL86]. The constraints net is represented on fig.2 [1].

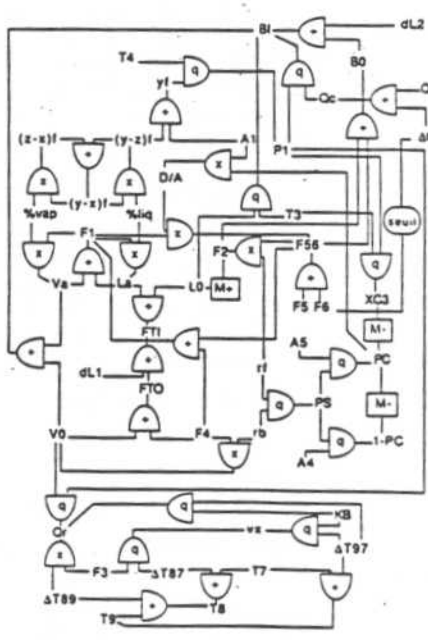


Figure 2: the qualitative model

[1] Future work on dynamic behaviour might imply QSIM-like simulation. However, our model, involving just tendencies of the parameters, could also fit the confluences equations paradigm [DeK84].

**Knowledge available**

In order to build this QP Model, different sources of knowledge about the process were available:

• The *pedagogical model* (henceforth called P-model) taught by domain experts. It connects some measured parameters with other synthetic and operational parameters, as internal reflux (LO) or the "separation index" (PS). They enable the operator to understand a situation and use control rules. The relations are material *balances* and oriented *influence rules* between parameters, based on naive physics (i.e. *everything else being steady*, if parameter x increases, then parameter y decreases).

• The *model of the numerical simulator*, that gives, for each time step, the values of every physical parameter. It predicts their evolution by iterative resolution of differential equations involving material and energy balance on each tray of the tower.

• *Physics* which provides equations, as for instance heat exchange in the reboiler, or thermodynamic knowledge about liquid-vapor and constituents concentration equilibria (P T V diagrams).

**Inadequacy of the simulator model**

In contrast with what is done in QP literature, the model cannot be extracted direclly from a functional diagram (as with electric circuits [DeK84]). If we represent the depropanizer as a distillation process with two trays, the component inflow/outflow analysis gives three types of equations (which are fundamentaly those used for the numerical simulation):

—material balance which involves the flows

—energy balance which involves the fluids enthalpies

—the balance of each constituent (C3 and C4)

The later, when mapped to qualitative equations were found inherently ambiguous and therefore useless. For instance, in the case of a stable feed for simplification (no flash change), they give qualitatively:

$$\partial A5 = VO * M(A4) - (F2 + F5) * A5$$
$$\partial A4 = VO * M(A4) + F4 * (1 - A4) - F2 * A5$$

where $M$ is a monotonic fonction

These equations do not enable any interesting deduction on the evolutions of A4 and A5, (qualities of extracted flows). For instance, if VO increases then F2 increases and there is a first ambiguity for each equation. Besides, tendancies on A4 and A5 produce crossed effects upon each other.

**Use of the P-model**

Qualities are the parameters to keep under control according to some production objectives. The P-model refers to operational parameters representing ill-formalized notions. For instance the parameter called "cut point" PC helps to infere the way the qualities evolve. The P-model describes the link between PC, the quality of the feed A1, the flows F1 and F5 (definition of PC); and the link between PC and the controlled "sensitive tray" temperature T3 (tower design).

Our approach has been to focus on this P-model, developped by engineers who truly understand distillation physics and distillation tower design. It provides useful (operational) and consistent explanations to the operator.

**Improvement of the P-model**

Unfortunately, the influence rules it relies upon are oriented relationships which must be analysed. The knowledge they emcompass must be captured into constraints, to take into account the "every thing else being steady" precondition. Other sources of knowledge had to be used :

• Some **physical knowledge** has been introduced to refine the P-model, as in the flash zone:

The *flash* is a good example of the way influences have been eliminated with the help of physical and thermodynamical knowledge. The flash splits the feed (with parameters flow:F1; temperature: T4; quality: A1) into a liquid (La) and a vapor (Va) flow under pressure condition (P1) in the tower. The material balance:

$$F1 = La + Va$$

is used and the other relations in the P-model are effects of T4, A1, P1 upon Va.

We studied the deep thermodynamic phenomena (shown in fig.3). A mixture of quality Z (here Z=A1), which temperature is raised at T (T=T4) under pressure P (P=P1), splits in liquid and vapor phases with concentration X and Y respectively. Thus, for the feed flow F1:

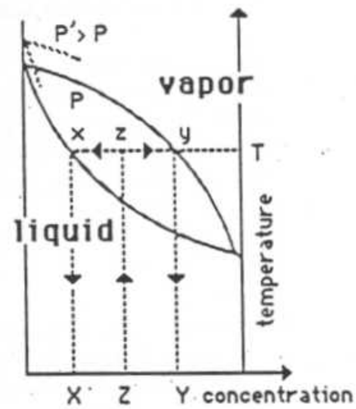


Figure 3 : representation of the flash

$$Va = F1\ \frac{z-x}{y-x}$$

We assumed $y$-$x$ remains steady, because at the flash zone, the liquid/vapor lense of fig.3 is rather large compared with possible perturbations on $z$-$x$ due to A1, T4 or P1. This approximation holds in the P-model. A last constraint links P (which induces the vertical position of the lense), T (which induces the level at which the flash split is done) and $y$.

• When available and useful, **physical equations** have been translated to qualitative ones. In the reboiler, the following equations describing the part of the efficiency factor and the energy transfer were mapped to qualitative constraints (see fig.2):

$$\frac{T8 - T7}{T9 - T7} = e^{-\lambda \frac{F3}{KB}}$$

$$Qr = \mu\, F3\ (T8 - T9)$$

## 4. Using the model

The QP model has been successfully validated in forecasting by comparison with the numerical simulator outputs. It is also a good tool for diagnosis: the key point in process control, according to experts and teachers.

□ The **prevision** procedure consists of two steps:

[1] Initialization: values of all the Perturbations Set parameters are first set to "steady". Then, the disturbed ones are changed according to the direction of perturbation. Active controllers are taken into account by setting the controlled parameters value to "steady".
[2] Propagation: the qualitative variations are then propagated through the constraint network using the qualitative algebra.

The trace of the propagation is a justification for the final qualitative state. The program produces a chain of inferences until further propagation becomes impossible.

An important point was to make multiple perturbations prevision always consistent: although some parameters may be ambiguous (i.e. stay unknown), the constraint network is never inconsistent. Ambiguities correspond to truly contradictory effects of different causes.

The prevision can only be performed from a stable state to another stable state. Qualitative simulation of transient evolutions remains a difficult problem, due to controllers behaviours and delays.

□ **Diagnosis** is detecting which parameters among the Perturbations Set have changed and in which direction. Remember that not all these parameters are measured.

According to the temporal perspective, diagnosis can be used in two different situations:

•*past diagnosis*, between two stable states, can use global balance equations. It is therefore more powerful, but the stability condition implies long spans of time before this diagnosis can be performed. The idea is that it can also be used for slow perturbations (e.g. reboiler loss of efficiency) when the equilibria are maintained.

•*present diagnosis*, between a transient state and a reference state, which must be stable relatively to hydrodynamic equilibria only. Global balance equations (encoding thermodynamic equilibria which are slower) cannot be used in that case. This allows the diagnosis to be obtained "sooner" but it is less precise.

The diagnosis procedure involves four steps:

[1] Data acquisition and translation: values of all the Sensor Set parameters are read from the simulator, then compared with a

convenient reference. A *fixed threshold* gives the qualitative translation of the quantitative variation.
[2] Propagation: as in prevision; this is one use of constraints.
[3] Consistency-checking: The values assigned to the parameters of the network in the propagation step are not necesserily coherent. Constraints must be checked for consistency; this is another use of constraints.
[4] Causes finding:
— if the previous step is successful (i.e. all constraints consistent), parameters among the Perturbations Set which have been assigned a variation value are suspected.
— if not, the entire chain of data acquisition (real value -(1)-> mesured value -(2)-> qualitative value) can be suspected: (1) because of a sensor failure, (2) because of a false quantitative/qualitative translation. This problem is a crucial issue for operational use of QP.

Diagnosis modules have been tested using the simulator as an approximation of the real process. They can generate new perturbation(s) hypotheses and validate past hypotheses in a continuous loop.

## 5. Conclusion and perspectives

A QP model of the depropanizer has been designed. It is the formalization and improvement of a pedagogical model used for operators training. Depropanization is one of the simplest distillation process but, according to experts, this QP model can be generalized to other kinds of distillation towers.

Different packages (prevision, present diagnosis and past diagnosis) have been built around the QP model. Their integration in a monitoring system of the process is under development. Managing several hypotheses of diagnosis and their validation through time is the way to use operationally the QP model and especially to deal with numerical data interpretation.

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