A NEW ERA IN PLANT DIGITALISATION

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Today's society is growing and learning in a new era, the age of computing. At the same time, year after year, new generations of central processing units (CPUs) and graphics processing units (GPUs) are coming onto the market, all linked to different machine learning (ML) algorithms that are gradually being integrated into society.

Most of the algorithms in use today were created decades ago. They are becoming increasingly standardised and available to everyone. This is due to their open-source characterisation and their ease of use thanks to the low-code philosophy. Even so, the current difficulty is not in the complexity of the mathematical formulation, but rather in how to integrate the mathematics into the solution.

At the same time, the hydrocarbon industry is not lagging behind and more projects are emerging which utilise this type of technology. The industry is seeing that the technology can be profitable and applied quickly. This article discusses the digital twin (DT) applied in hydrocarbon processes. It will explain what these types of applications are and where they come from, and will explore different types of this technology.

What is a DT and where do they come from?

During production, the aim has always been to make inferences on process variables. This allows access to more information with which to make decisions. A simple economic balance of outputs minus inputs is already an inference of profit. However, this article will discuss the process and control part. Let us start with a very simple example: water boils at 100°C at atmospheric pressure. What happens if water is boiling at 110°C using a pressure cooker? With a single thermometer, we can know the pressure – in this case it would be 1.4 atm. A very common inferential in the hydrocarbon industry is the composition in distillation columns. In this case it gets more complicated. Let us assume a binary mixture, e.g. propane and propylene. What we know is, each tray of the column is boiling, so if we measure pressure and temperature on that tray, we can find out the composition of this mixture. This is because there is only one mixture boiling at that pressure and temperature.

While this sounds ideal, real plants are not that simple. There are always more components, the instrumentation does not work as it should, and there can be moments when operators are not in balance. In these situations, one must look for more complex solutions. There are many options, and they all have their pros and cons. There are three main solutions:

- The first solution is to correlate directly with plant data. This has its merits, as it directly uses historical data from the actual plant. However, only using data is not always a good thing. This is because one can only correlate something that there is already historical data of. Therefore, the predictions will get increasingly inaccurate as they move away from the correlated data zone. To complete these regressions, conventional multivariate calculations can be used, such as the typical polynomial fit. Alternatively, ML model training can be taken.
- As a second solution, commercial simulators can be used. These already include thermodynamic packages and most of the objects to be simulated. However, they will require a model to be built for the simulation. This model can be used to generate all the states in the plant (e.g. high, medium, low feed, high pressure, low pressure). This includes all the states that the process can have depending on the independent variables. With these results, correlations can be applied and the inference that the operator is looking for can be calculated. This will give better solutions than correlations which use only the historical data of the plant, since there will be more samples outside of the normal operation parameters.
- The third (and most accurate) solution is to connect the model to the historical pipeline. This model can be a dynamic or steady state, depending on whether the operator is interested in transitions or not. This consists of feeding the model with all the inputs. These inputs are mainly process variables (PV), set points (SP), outputs from controllers (OP), laboratory data and online analysers. This DT of the plant is the most accurate and

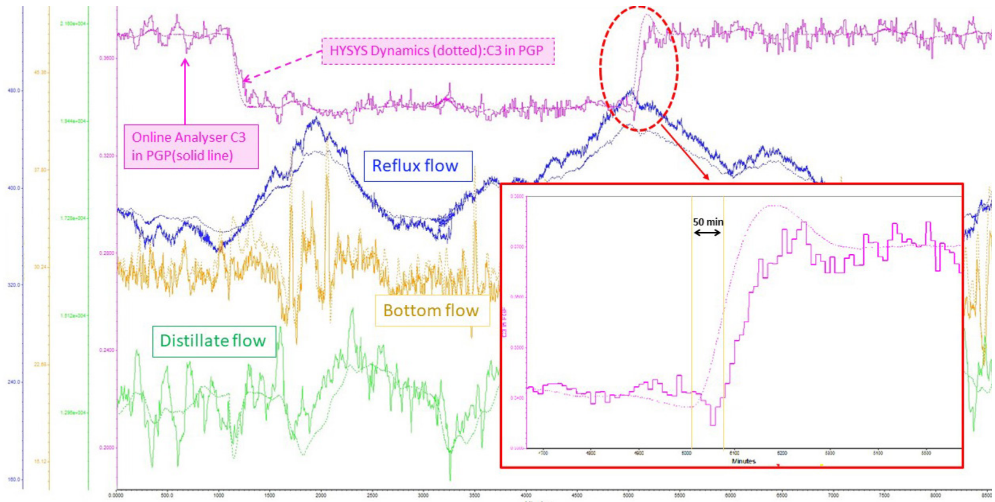

Figure 1. Comparison of data: digital twin data (dashed) and plant data (solid).

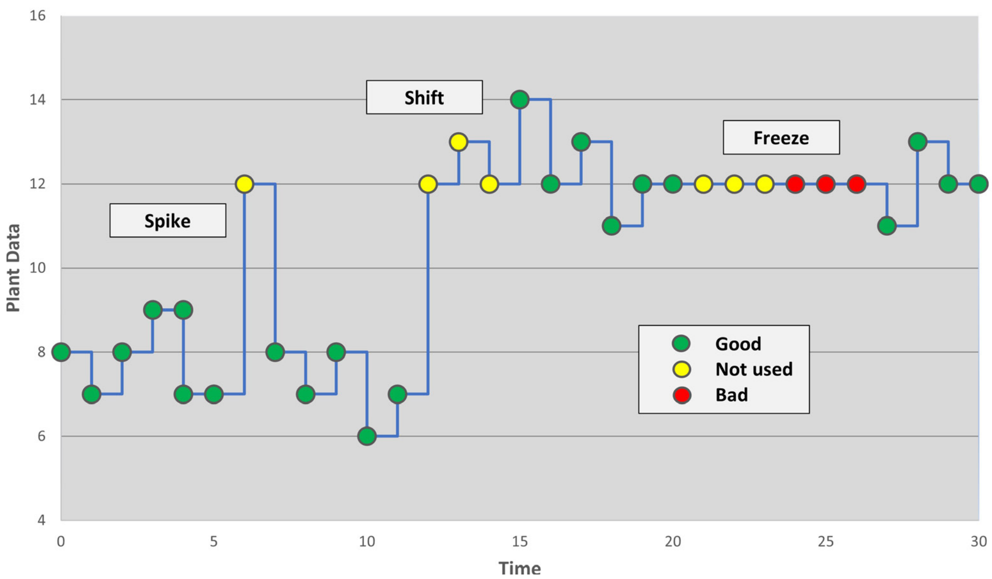

Figure 2. Graphical description of some data processing in the digital twin inputs.

will give the operator more scope for optimisation and control. The only problem with this is that unlike the other solutions, it is necessary to build a more complex model and integrate it into the plant system.

For example, in a distillation column, it is interesting to know the composition of the distillate and the composition of the bottoms for its correct operation. But beyond that, the price of an online analyser project can be around €500 000. Moreover, an online chromatograph takes samples every 10 - 15 minutes and is also affected by the dead times of the tubbing. This means that a lot of control and optimisation margin is lost, especially in continuous processes that run non-stop for years.

At the same time, inferences are not only used for operators, but more usually for advance control applications. They tend to be widely used in predictive variable controllers (MPC). These are very well integrated in the industry as their implementation is relatively feasible and usually gives good results. Finding key hidden variables and replacing controlled variables with more optimal ones can improve control and production.

How is a DT developed from a dynamic model?

DT projects have a similar development structure to MPC projects. As a first phase, it is very important to have a clear understanding of all the instrumentation and control in the plant and to make an analysis of the historical data to detect that everything is working correctly. For this step, simplified steady state models are usually developed as they allow the operator to close energy and material balances.

Once everything is clear, the independent variables of the process have to be defined. These variables are the manipulated variables (MVs) and the disturbance variables (DVs) – mainly those that will affect the process and depend on time (SPs, boundaries, OPs).

Thereafter, a dynamic model is built and validated with historical data (10 to 30 days and 5 - 60 seconds sampling). With this model, it is possible to know how well the model fits and where to focus the efforts to match the simulation with the plant data. Figure 1 shows a model that has run with the plant data. The advancement of values in time compared to online chromatographic samples can be seen. Nowadays, as a result of computational power and with the help of automation algorithms, it is becoming easier to match these commercial models to historical plant data.

As the DT model is fed with plant data – which is affected by all the physical phenomena that can affect the instrumentation – it is necessary to make a treatment to ensure that the plant data is consistent. Usually, different transformations are applied to deal with instrumentation failures, spikes and noise (Figure 2). Plants and their behaviour are dynamic, so it is necessary to differentiate between the changes they undergo. On the one hand, the system has to be able to deal with unknown DVs, and on the other hand, it has to deal with physical changes in the equipment (e.g. fouling, clogging of equipment, failures). Therefore, it is important that the model reconciles and monitors these changes in real time. If the impact of an unknown DV is significant, the DT will not track the plant and in this case it is recommended to measure that paticular DV and potentially incorporate it into the MPC controller.

Some logic has to be applied to deal with certain plant scenarios, for example, switching from pump A to pump B, starting parallel trains or the shutdown of the plant. Finally, with the model already developed and tested, the variables to be exported are defined and connected to the realtime database of the plant. A subsequent validation is carried out with the system connected, first in open loop to monitor, and then in closed loop with the MPC to optimise, as shown in Figure 3.

Benefits

DT technology offers a number of benefits, including the following:

- Inferential: the DT can calculate pressures, temperatures, flow rates and compositions for each stream in the plant, or for each tray in a column. This data can be used by MPC controllers or operators, or backed up by online analysers.
- Alarm warning: having a first principles model as the basis of the DT calculation allows operators to have a comparison between what should happen and what actually happens in the plant. With this insight, operators can predict if the process and instrumentation is operating efficiently.
- 'What if' scenarios: DT always operates in the current state of the plant and can therefore be used by engineers to evaluate a change (e.g. set point, control parameters,

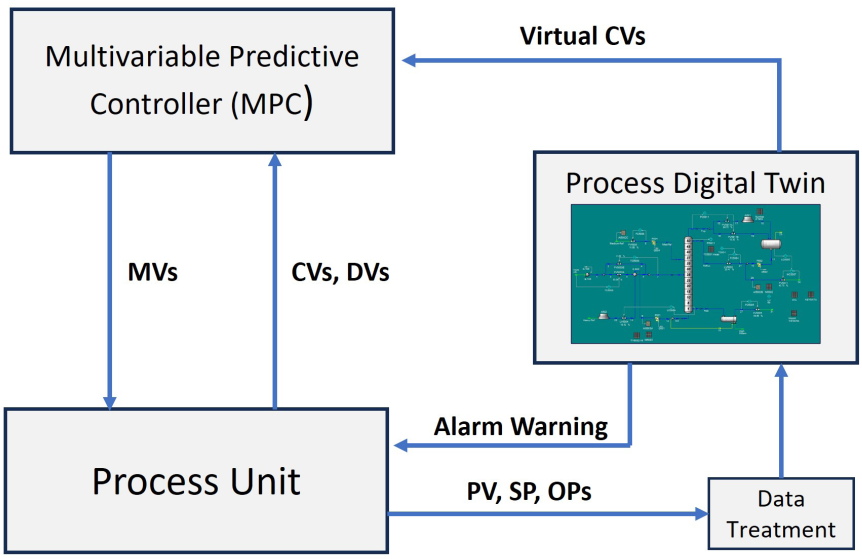

Figure 3. Simplified flow diagram between an MPC, DT and the process unit.

equipment parameters, boundary conditions) before it is actually taken in the plant.

These types of projects are currently new in the industry and are being applied in different areas of the hydrocarbon sector. One of these applications is at the start of greenfield plants. Once the plant has started up, there are many unforeseen events and it is likely that equipment may not be working as designed. This can be due to multiple reasons including control settings, diferent boundaries, process anomalies, etc. Through DT, operators may be able to detect these errors, correct them, or leave them planned for future implementation of improvements. This is an application that allows the detection of these problems in a fairly simple and fast way, meaning operators can avoid living with these problems for years (as plant myths) until they are eventually realised and resolved at a much later date.

MPCs work by controlling a series of controlled variables (CVs) in a zone defined by an upper limit and lower limit. Most of the CVs in MPC controllers typically correspond directly to the plant instrumentation and online analysers.

Some of the CVs are labelled as 'critical CVs', meaning that the MPC switches off if any of these fail. The DT can provide backup values for these critical CVs. At the same time, there are situations where it is interesting to have CVs that are not measured in the plant in order to optimise. As previously mentioned, it is difficult to quantify the optimal instrumentation needed in the plant. For example, a deethaniser distillation column can have different control philosophies. The objective is always the same: to separate between C2s and C3s. But depending on the process, the reboiler duty will be increased to avoid C2s in the bottom or, on the contrary, the condensation will be increased to avoid C3s in the head. This creates a situation where operators will have to decide what to increase and what to sacrifice. Normally, operators only have online composition analysers where they need to meet the product specification. With a DT, operators can infer composition that is not measured and, therefore, control the column in the most optimal way.

The dynamic model of the DT is also used to perform other offline tasks. One of these tasks is to improve the performance of MPC applications. The dynamic models are used to calculate the true process gains (CVs vs MVs/DVs) for the whole operation range of the plant. With this data, the APC engineer can define the best MPC solutions (models validity, models multipliers, multiple models, etc).

Another task is to use the dynamic model to generate virtual data to train deep reinforcement learning (DRL) controllers. This virtual data is provided for the whole operational envelope of the plant, and the data is not contaminated by unmeasured plant perturbances or noise.

Conclusion

New technologies are allowing well known dynamic process simulators to have even more potential than they currently have. They allow more robust systems to be built, which are more powerful and can have new useful functionalities. The prediction of plant behaviour, the improvement of safety, and the maintenance of equipment are critical points to which more resources are being dedicated continuously. DTs are an extremely valuable tool which can be used to improve the operation of plants and provide assistance to plant issues.