DIGITAL TWINS FOR THE GEOTHERMAL INDUSTRY: THEORY AND PRACTICE

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Keywords: *Digital twin, geothermal industry, dynamic geothermal plant modelling, decoupling model*

ABSTRACT

The term ‘digitalisation’, currently popular in many industrial sectors, refers to the construction of computer models intended to improve production and efficiency. The ‘digital twin’ can be considered as one of the core concepts of the digitalisation, and while still at the conceptual stage for many manufacturing operations, there are examples from the power industry - such as the Digital Wind Farm from GE Renewable Energy used to optimise turbine operations, and improved maintenance planning of the EDP (Energias De Portugal) Alqueva II hydro power plant using a Digital Hydro Plant. In this paper, we will present results from our recent two projects on the concept of linking digital twins within the NZ geothermal industry. The first is dynamic modelling of a geothermal power plant, and the second is an exploration of the economic optimisation when coupling both process and reservoir simulators to provide accurate prediction of both reservoir and plant behaviours over the life time of the plant. The gaps between theory and practice are summarised and the anticipated future trends in digital twins for the benefit of the NZ geothermal industry are also highlighted.

1. INTRODUCTION

Recent advances in information technology and associated hardware have now made it possible to construct useful models in a safe virtual world that simulate physical manufacture, enable model-based control schemes, allow remote operation of industrial facilities, and cooperate with neighbouring manufacturers to improve the over-all production and efficiency of almost any industrial plant. With state-of-art developments of information technologies, such as wireless high-speed data transmission, big data analytics, Internet of Things (IoT), cloud computing, and artificial intelligence (AI), interactions between the physical and virtual spaces are more active than ever before.

The term *Digital Twin,* (DT), is now generally accepted as referring to a high-fidelity digital mirror of the actual plant. Consequently the DT can be considered as one of the core concepts of the industrial digitalisation drive. The term was first articulated by NASA to describe the development of advanced high fidelity simulations used for the purposes of certification and flight testing (Glaessgen and Stargel, 2011). But of course the idea of employing a model for design, control and optimization arose much earlier. However DTs in the context of process industries has been called the next generation of process simulations (Lu, *et al.*, 2020). Today, the DT terminology is commonly used by researchers and industries to describe process modelling attempts related to different manufacturing operations.

The application of DTs in the power industry has attracted significant industrial attention, and several companies have set up DT projects. GE Renewable Energy (GE, 2016) introduced the digital twin concept into the wind power industry. Through the use of GE Predix platform, the Digital Wind Farm DT has been built to optimise turbine operation and increase the efficiency of power generation. EDP (Energias De Portugal) improved repair planning for the Alqueva II hydro power plant, with the assistance from the GE Renewable Energy’s Digital Hydro Plant (GE, 2018), which is an advanced digital analytics platform for maintenance of hydroelectric plant at lower cost and improved efficiency. Siemens (Siemens, 2017) has created a DT for the Finnish power transmission grid. The key benefit of this DT is that the grid model has the capability to analyse itself, reducing the time required of analysts to develop software or build model cases. In a similar manner, Prince-Pike et al (2012) developed a dynamic model of every generator for the entire electrical transmission grid for New Zealand which was used by the national grid operator to efficiently manage the electrical reserve market.

The DT also makes time and provides assistance to making decisions based on real-time graphics data. Osinde *et al.* (2019) conducted research about process modelling of geothermal drilling systems using a DT for real-time monitoring and control. They proved that the DT model of the geothermal drilling operation can closely mimic physical operation.

Although the DT concept is gradually being implemented in many industries such as the power, food, oil & gas, and automotive industries, (as reviewed in Qi & Tao, 2018), there is little reported specifically on application in the geothermal industry. In this paper, we will briefly introduce DT definitions and provide two examples of DTs for the NZ geothermal industry.

2. DIGITAL TWINS IN THEORY

2.1 DT definition

Credit for the term `digital twin’ is given to (Grieves, 2014) who divided the system into 3 parts: a physical product, a digital counterpart, and the connection that links the physical and digital parts together. In 2010, NASA (the US National Aeronautics and Space Administration) published a definition of a spacecraft DT and described its functions during space exploration missions (Shafto *et al.*, 2010). In 2011, the U.S. Air Force explored the application of DT in aircraft structural life prediction (Glaessgen & Stargel, 2012; Tuegel *et al.*, 2011).

With the development of big data analytics, artificial intelligence, the internet of things (IoT) and other new information technologies, there have been many leaps-forward in the field of data collection, transmission and processing. The data are both from the real-time sensors in the physical space and the simulation results in the digital space. These new IT technologies laid the foundation for the application of DT.

The digital twin concept has received lots of attention and has been introduced into many industrial fields. Manufacturers from various industrial areas have used this new concept for better monitoring real facilities and saving costs in repair and operation. For example, PACCAR used DT technology to predict the maintenance of truck engines based on the data from the sensors in the real engines (PACCAR, 2019). In the oil and gas industry, DT technology makes the reduction of downtime and risk from plant maintenance possible. For most of their descriptions, the DT is a framework of dynamic data connection between the physical existence and the virtual counterpart. With the new IT technology, it provides realistic optimisation and prediction through the lifecycle of one product. The DT was listed in "Gartner's top 10 strategic technology trends" for 2017-2019 (Panetta (2016 and 2017); Ross (2018)).

2.2 Digital twin structure

One characterization of the DT was proposed by Kritzinger *et al.* (2018) who considered not only the plant and model, but also considered the interconnections between the two as shown in Figure 1.

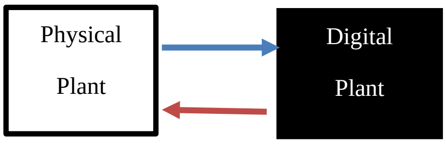

Figure 1: DT structure

For an operational DT to be created there are three main components that must be developed and then integrated.

1) Physical Plant: This physical part also contains the sensors and automated control values that are used by the DT to monitor (gather information) about the process and to act on the production plant.

2) Digital Plant: The most crucial part of an operational digital twin is the digital plant which consists of a digital model that can take information in "real time" and suggest necessary control actions.

3) Digitalisation Infrastructure: an operational DT should have the digital/IT infrastructure that provides bi-directional connection between the real plant and its virtual twin.

Fuller *et al.* (2020) also carefully considered what makes the digital twin concept noteworthy above and beyond a standard process model. Our approach in this study has been to extend this idea where we characterize the models both by how they are used, but also by what inputs they require and outputs they deliver.

We propose that the various models are characterized as shown in Figure 2. Initial models are constructed using domain specific information, possibly from well-known correlations and an understanding of the underlying physical-chemical phenomena. These 'textbook' models are then validated using offline measurements to better tailor them to the specific plant and conditions.

The third level of model complexity is where this model is continually refined using the current actual operating data. In this case for example parameters such as heat exchanger coefficients can be updated. It is at this point that the demands for interconnectivity between the model and plant become significant in order for the model to be "living", in the words of Liu *et al.* (2018). Following the characterization of Fuller *et al.* (2020), this is known as a Digital Shadow, and it is important to note that the model outputs here are not automatically fed back to the plant, although this does not preclude manual intervention.

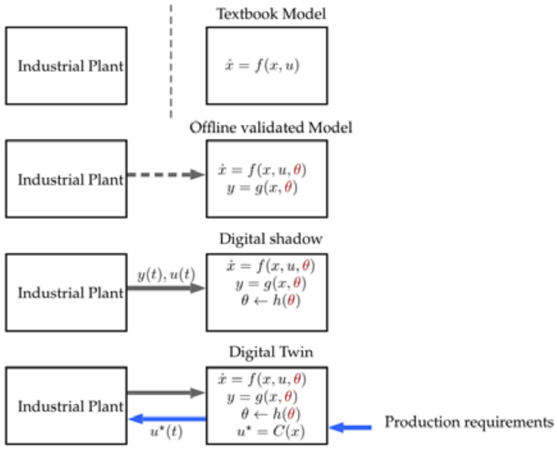

Figure 2: Characterising the different roles process models can play in an industrial production environment.

Finally we come to the full *digital twin*. Here the model is also continually refreshed with the current operating data, but now the outputs of the model are continuously fed back to the plant, such as say the optimal control action derived from a model based controller. One of the key insights from Fuller *et al.* (2020) is the realization that the system model, something that historically demanded the most effort and attention, is actually only now part of the package. Of increasing importance is the connectivity infrastructure and accompanying industrial IoT, the associated data analytics, and ever-present data security. The DT makes it possible to discover what is happening and will happen immediately in the physical plant. The changes in physical plant will be directly reflect identically in its virtual counterpart: digital plant or DT and vice versa.

2.3 Related concepts to DTs

The fourth industrial revolution is the digital transition that has been occurring since the middle of the 20th century. Its character is the combination of technologies that is blurring the boundaries between the physical, digital domains. The fourth industrial revolution is affecting almost every industrial field, even the lifestyle of people, and the next big technological leap is brewing up. The main pillars of the fourth industrial revolution are the technologies related to the concept of the DT.

The Internet of things (IoT) is the concept of the connected network of physical facilities. Through the IoT, instant data communications between these physical objects can be achieved. Numbers of objects or plant units are interconnected with each other by wireless and high-speed network. Therefore, information about the real-time state of one object is ready for objects upstream and downstream; also, the feedback occurs very quickly. Large quantities of data are provided for analysis in the digital space. Hence, the DT is the virtual counterpart of the connected real object.

2.4 Limitations of DTs

Cost is mostly the first consideration for any DT project. Building a DT involves constructing a complex set of software models to communicate with and simulate the real process online. This is a time-consuming and labour-intensive process. The setting up of the DT also needs lots of high performance of hardware, such as a high-speed communication network, high-performance computers, and secure big data storage space, which are costly at present. Therefore, the application of DTs are typically limited to complex processing, high-value equipment, or high-profit processes.

The information security risk is another consideration for these enterprises that need to be digitalized via digital twin technologies. To make sure the data from the DT, or the DT itself is out of risk of cyber threats is a serious challenge. Intellectual property rights also should be protected to establish an efficient and fair development environment for DT technology.

The lack of standards and support platforms is the third limitation. Although some big companies, such as GE, Microsoft, and Siemens, are improving their respective DT services, there is not a standard system to follow for leveraging existing DT solutions on one platform. Instead isolated DT technology tools are developed to deal with individual issues from different industries or fields of endeavour. A DT-development framework could make the growth of this new technology more efficient and standard.

Increasing the participation of workers in the DT is a necessary step in applying it to the actual 'plant-floor' level. To increase DT application in the real running plant, a comprehensive understanding of the DT is necessary for engineers, designers and researchers who are involved in this new style manufacturing system. The human-machine relationship is also a new issue in psychological research.

3. THE DIGITAL TWIN IN PRACTICE

Our first DT example is a dynamic model for a NZ geothermal organic Rankine cycle (ORC) plant. Following the classification given in Figure 3, this model would be termed a Digital Shadow. Our second DT example is a comprehensive model that incorporates both a geothermal reservoir and geothermal power plant and is also a digital shadow.

3.1 Dynamic modelling for geothermal ORC plants

The almost ubiquitous approach when constructing geothermal ORC models is to use semi-rigorous, mass and energy balances relations constrained with thermodynamic relationships. The resulting differential-algebraic equation system is solved numerically. Good examples of this approach are seen in papers by Quoilin *et al.* (2011), Felgner *et al.* (2011) and Sun and Li, 2011. One apparent exception to this approach was illustrated by Zhang, *et al*. (2012), which used a much simpler black-box transfer function model, although it should be noted that this in turn was derived from an earlier first-principles dynamic ORC model (Zhang *et al*., 2012).

3.1.1 Modelling using VMGSim

The plant-wide dynamic model in this example was built by connecting together pre-built unit operations present in the VMGSim simulator (VMGSim, 2020). These included heat exchangers, pumps, expanders, separators, valves and controllers. These unit operations were connected together in the appropriate order to build a model of an existing ORC plant. A screenshot from VMGSim showing the model layout can be seen in Figure 3.

The specifications for the model were based on design temperature, pressure and flow values in the plant documentation. For the heat exchangers this includes pressure drop and overall heat transfer coefficient values (UA values). For the pump the performance curves from the plant documentation (head vs. flow and efficiency vs. flow) were imported into VMGSim. The expander performance curve was not available, so a built-in curve already available in VMGSim was used. PID controllers for the primary control loops were implemented in the model with the same tuning parameters (gain, integral time and derivative time) as the real plant. An air cooler unit operation with built-in relationships for fan power and air flow is not available in VMGSim so a heat exchanger unit operation was adapted for this purpose. The use of the heat exchanger unit operation present in VMGSim as an air cooler should be validated in the future to determine if it can adequately model a real air cooler.

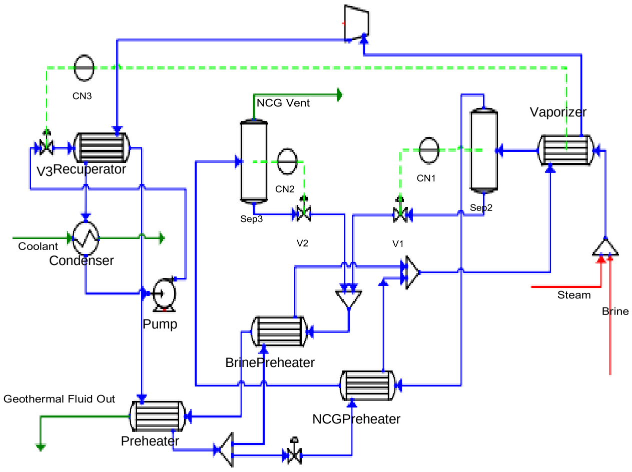

Figure 1: A schematic of an ORC model in VMGSim

3.1.2 Modelling of heat exchangers within ORCs

One area where there is some variation in the ORC models presented in the literature is how heat exchangers are modelled, particularly their heat transfer coefficients. Some papers (Jung and Krumdieck (2013) and Ghasemi *et al.* (2012)) took a comprehensive approach to determining the heat transfer coefficients based on the underlying heat transfer mechanisms. Others calculate the heat transferred directly using pinch analysis (Wang *et al.*, 2013) or use predefined heat transfer rates from existing systems (Sun and Li, 2013). Other papers do not supply information about heat transfer coefficients, and could be using constant overall heat transfer coefficients in their models, an example being the model being validated in this paper.

In order to construct an accurate heat transfer model it is necessary to examine the literature on heat transfer for the conditions found in the plant's heat exchangers. The non-condensable gas (NCG) preheater was chosen for a more detailed analysis so it could be compared to the simpler model used in the overall plant model. On the working fluid side of the heat exchanger there is liquid phase sensible heating under turbulent conditions and on the geothermal side of the heat exchanger there is two-component, two-phase condensing under stratified two-phase flow conditions.

3.1.3 Model validation

Before a simulation model can be used for any purpose, we must ask a simple question: is the model valid? If a model is not valid, then any results based on the model will be unreliable. In fact the two significant concerns for any simulation are verification and validation (V&V). Definitions for V&V are given in the classic simulation text book (Law and Kelton, 1991) as "verification is determining that a simulation computer program performs as intended, i.e., debugging the computer program…. validation is concerned with determining whether the conceptual model (as opposed to the computer program) is an accurate representation of the system under study". The conceptual model of a process is a formal definition of the system under consideration in logical or mathematical form, typically comprising the underlying theoretical equations. In this paper, we will focus on the validation of our model as we are using commercial, verified software.

Four methods for model validation proposed by Sargent (1996) are: conceptual model validation, data validation, white-box validation and black-box validation. In this paper, we will use two model validation methods: white-box validation and black-box validation. White-box validation focuses on checking that the individual components in a model correspond to reality. In black-box validation the overall behaviour of the model is evaluated. The same inputs which enter the real processes or systems will be tested on the model, and the outputs from the real processes or systems and the model will be compared.

VMGSim simulation software is the platform for ORC modelling; the existing unit operations present in the software have been verified by the commercial software developer. However some of these unit operations may not be able to properly model the ORC plant under consideration. Using the white-box validation method, we will check whether the heat exchangers can adequately model the real units, using the NCG preheater as a test case. For the black-box validation, the outputs from the real ORC plant (historical plant data) under consideration will be compared to model outputs for the same set of input conditions.

White-box validation

For the white-box validation, the NCG preheater was modelled in VMGSim at design conditions by dividing it into five horizontal segments in sequence. Using the new values for the heat transferred in the sections, new outlet temperatures were calculated for the NCG stream within each segment of the NCG heat exchanger and these temperatures were contrasted with the results from VMGSim. The temperatures are presented in Table 1.

Table 1: NCG output temperature for the VMGSim and first principles (white-box) based models

Segment	First Principles based model NCG Output Temperature (°C)	VMGSim NCG Output Temperature (°C)	Absolute Difference (°C)
1	167.95	165.82	2.13
2	161.63	160.84	0.79
3	152.10	153.52	1.42
4	136.48	141.96	5.48
5	113.42	122.00	8.58

Black-box validation

For the black-box validation, the plant-wide model created in VMGSim was run using 800 minutes of real historical plant data as the input. Certain output variables that are monitored in the real plant were recorded from VMGSim and compared to the same output variables from the historical plant data.

The inputs into the VMGSim model were the steam temperature, brine temperature, steam mass flow rate, brine mass flow rate and the ambient temperature, which is modelled in VMGSim as the temperature of the coolant running through the condenser. The output variables were the vaporiser percentage liquid level, the turbine power output and the working fluid temperature outputs of all six heat exchangers (preheater, brine preheater, NCG preheater, vaporiser, condenser and recuperator).

Table 2 shows a summary of the results from the black-box validation. By contrasting the mean value of the residual against the mean of the real value it is possible to gain some idea of how well the model approximates the real plant. The standard deviations will give some indication as to how well the model behaves under different input conditions.

Table 2: Statistical summary from the black box validation

	Mean real value	Mean Residual	Standard Deviation of Residual
Vaporiser Outlet T [C]	161.03	9.79	1.60
NCG Preheater Outlet T [C]	151.70	14.36	0.95
Brine Preheater Outlet T [C]	149.64	16.39	1.40
Preheater Outlet T [C]	92.84	-1.27	1.14
Condenser Outlet T [C]	27.70	1.62	0.83
Recuperator Outlet T [C]	53.67	7.60	0.79
Gross Power Output [MW]	16.84	0.62	0.27

An examination of the residual values for the heat exchangers shows that, except for the preheater, the modelled outlet temperature of the working fluid is higher than in reality. The brine preheater shows the largest residuals are close to 20 °C, followed by the NCG preheater at around 14 °C, the vaporiser at around 10 °C, the condenser up to 3 °C and the preheater which had a lower temperature than the real data by 2 °C. This indicates that for the given input conditions, assuming constant heat transfer coefficients based on design data tends to overestimate the heat transfer coefficient. These differences will also affect the accuracy of the power output prediction; residual values for power output is up to 1 MW (the mean total power is 17 MW).

This example shows important trends are captured but more work to improve the model quality is required before the digital shadow of geothermal power plant can be used to help improve the plant efficiency.

3.2 A coupled model for the geothermal industry

This case study is to demonstrate the ability to couple a subsurface reservoir model with a surface facilities model, for a more accurate simulation, especially in the long term. As the temperature of the geothermal fluid decreases, dissolved silica comes out, resulting in the formation of scale. Scaling which occurs throughout the plant, reduces both flow and heat transfer coefficients, and as a result a decrease in both power output and efficiency can be observed (Zarrouk *et al.*, 2014).

Geothermal fluid mass flow, pressure and temperature data are passed between AUTOUGH (is a geothermal simulator based on on a modified version of TOUGH2 developed by the University of Auckland) and VMGSim, where both the wellbore and plant are simulated respectively. Brine injection data is passed back to AUTOUGH from the VMGSim plant simulation.

By combining the both simulation models, the CO_2 depletion within the reservoir can be studied and the effects can be characterized. A reduction of CO_2 produced for a binary plant promotes heat transfer but at the cost of increased pressure drop within the wellbore, and, as a result, the power generation decline occurs much earlier than anticipated. The proposed coupled model adds additional benefits to the modelling process that supports the optimization of both reservoir and surface related activity. Addition of historical ambient air temperature allows for more accurate results but at the cost of increased simulation time, but, in turn, allows for more accurate economics when conducting FEED (Front End Engineering Design).

Figure 4 shows the simulated difference between plant power with, and without coupling the models. The model simulations begin at year 15, the year in which the forecast of the reservoir begins (01 Jan 2012).

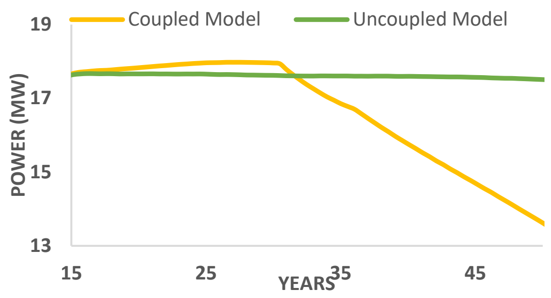

Figure 2: The plant power output over the 50+ year working life at a fixed ambient temperature as predicted using both coupled and uncoupled models.

The power in the coupled model initially increases due to decreasing CO_2 production as a result of reservoir depletion. This causes better heat transfer in the vapourizer leading to increased power generation. After excessive CO_2 production, plant power begins to decrease because CO_2 influences the formation of vapour in the wellbore. CO_2 increases the vapour pressure of the fluid, therefore the mixture forms two phases deeper in the wellbore compared to when CO_2 is not present in the fluid. CO_2 also inhibits the formation of water vapour which reduces lost energy caused by forming steam which is not beneficial for a binary plant. Feed zone data such as mass flowrate, temperature, pressure and composition are sent for process simulation, with similar injection data generated and sent back to the reservoir simulation.

Figures 5 and 6 show CO_2 dissolved in the brine simulated in the wellbore model. The wellbore model uses the Duns and Ros pressure drop correlation as that gave the best fit compared to actual data. As CO_2 is depleted from the reservoir, heat transfer in the vaporizer is improved resulting in increased power. As CO_2 is a heavier molecule, the average velocity is slower than that of water vapour, and a result causes a lower pressure to drop due to friction.

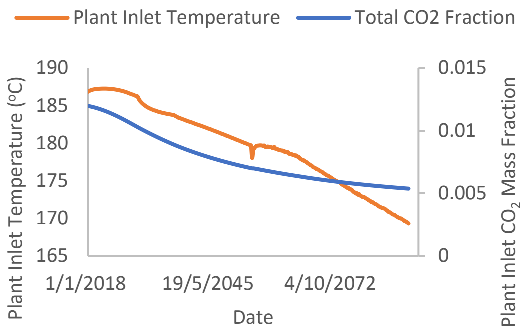

Figure 3: Plant inlet temperature with changing dissolved CO_2.

Typically, during forecasting, the injection rates and temperatures are kept constant. As a result, temperature and flow changes due to both fouling and natural decline are not accurately represented. The study conducted on both integrated and standard models shows that there is a difference between both methods as a result of both ambient temperature and reservoir chemical changes.

This example shows the feasibility of the coupled model for both power plant and reservoir and potential benefits for forecasting operations. However, due to lack of industry data, the coupled model has not been fully validated, which is necessary for building reliable/robust DTs for implementation in the geothermal industry.

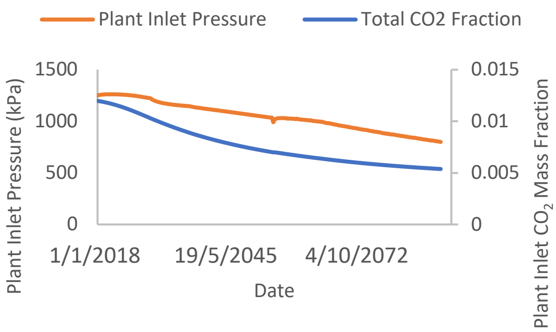

Figure 4: Plant inlet pressure with changing dissolved CO_2.

4. CONCLUSIONS

This paper illustrates the potential benefits of using digital twins (DTs) in the geothermal power industry. Following the commonly accepted definition, a DT comprises both a plant model, and the data conduits linking the model to the true plant.

The appropriate complexity of the model depends on the intended application. In this case, it was the economic viability of the plant over the entire 50+ year life, and given this extended period, it was then necessary to model both surface unit operations, and the sub-surface phenomena.

ACKNOWLEDGMENTS

We acknowledge the Heavy Engineering Research Association for finance support to a PhD research project and the Top Energy for technical support.

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