SMART MANUFACTURING: APPLICATION TO AN INDUSTRIAL SCALE STEAM-METHANE REFORMER

Ankur Kumar, Michael Baldea and Thomas F. Edgar*
University of Texas at Austin
Austin, TX 78712

Abstract

Manufacturing industry has witnessed a gradual transition from being a heuristic-driven labor-intensive set of processes to a sophisticated set of automation and model-driven processes where each operation unit in the production chain is automatically controlled and operated at a preset optimum regime. While incremental improvements in overall manufacturing efficiency have been steered by advances in computational algorithms, many of these enterprises, however, can still be characterized as being a collection of 'islands of automation' and being 'rich in data but poor in knowledge'. This can be attributed to sub-optimal usage of available process data and neglect of enterprise-wide analysis. There are several systemic factors which contribute to such myopic treatment of manufacturing operations. In addition, other factors have kept medium and small-scale manufacturers from leveraging even the currently available automation tools. In this paper, we explore these factors in the context of smart manufacturing (SM) as a vehicle for a paradigm shift in the manufacturing industry. A case application of SM in a hydrogen manufacturing plant as an industrial example is presented where integrated use of advanced sensors, high-fidelity and reduced-order models, high performance computing, and data management and visualization tools paved the way for plant-wide energy usage reduction.

Keywords

Smart manufacturing, Infrared pyrometry, Steam-methane reformer

Introduction

Manufacturing entities continuously evolve to stay competitive in the face of constraints such as environmental regulations, labor cost and availability, raw materials feedstocks and demand uncertainty, which dictate the production economics. Sophisticated process modeling and control technologies are employed to increase the production efficiency by optimizing individual process units in the production chain. However, the overall production often remains sub-optimal due to the presence of these "islands of automation" which operate unaware of the exogenous factors such as disturbances in supply chain. This can be overcome by application of manufacturing intelligence across the production chain and an IT infrastructure that facilitates such an application. A coalition of companies, universities, manufacturing consortia (SMLC) have proposed Smart Manufacturing (SM) as the vehicle for accelerating manufacturing innovation and achieving the transformational productivity gains in the 21st century (SMLC, 2011).

For illustration, consider the hydrogen (H_2) manufacturing industry where natural gas (methane) is converted into hydrogen in large furnaces, also called steam-methane reformers (SMRs). It is a highly energy intensive process and consumes ~ 10^5 GJ per day. Mathematical modeling of SMRs becomes a crucial tool for achieving high energy efficiency. The models can be either high-fidelity (e.g., using computational fluid dynamics), data-driven (and typically low-order) empirical models, or a combination of both. However, the development of mathematical models needs to be accompanied by online deployment for automation and control purposes. The latter must be supported by an IT infrastructure, that includes, i) capabilities for acquiring appropriate process data via systematically placed sensors, ii) adequate high-performance computational resources for just-in-time computations, and, iii) a user-friendly visualization interface for operator use. The model-based computations are themselves a sequence/workflow of calculations being executed in series or parallel. Seamless interactions between these different layers require an appropriate IT infrastructure that allows the intensive computations to be performed on cloud and intercommunications between various components of the workflow, and provides appropriate database management capabilities. Moreover, rapid adoption of such practices demands that such an IT infrastructure should be easy to use and deploy. These requirements constitute the natural and essential form of SM (Davis et. al., 2015). In this paper, these aspects of SM and their adaptation to a H_2 manufacturing plant, along with the benefits obtained therefrom, are described.

H_2 Plant and Steam-Methane Reformer: A Primer

Figure 1 shows a simplified H_2 plant; natural gas undergoes endothermic reforming reactions in a reformer furnace (with dimensions 16 m X 16 m X 12.5 m). After heat recovery, the syngas product passes through a shift reactor followed by H_2 separation via pressure swing adsorption (PSA). Energy released from combustion of fuel (natural gas) in the furnace supports the reforming reactions. Figure 1 also shows the furnace interior, with several tubes suspended vertically. Reforming reactions take place inside these catalyst-filled tubes. Note that natural gas is used both as fuel (passes through burners placed at the top of the furnace) and process feed (inlet to reformer tubes). The process gas temperature inside the tubes increases from about 800 K to about 1100 K and the burner exhaust gas is typically in the 1300 K range.

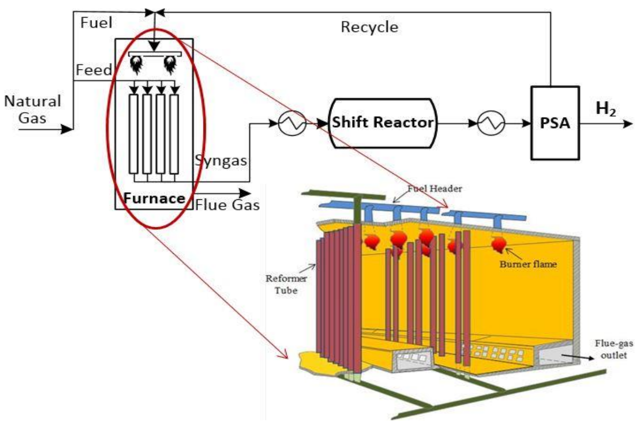

Figure 1. H_2 plant process and SMR furnace

Process Energy Efficiency

The H_2 plant energy efficiency is greatly influenced by the furnace tube temperature distribution. Higher operating temperature leads to greater H_2 yield (due to endothermic reforming reactions) and higher steam production following heat recovery, and consequently, lower energy consumption per unit H_2 produced. The prescribed operating temperature of the reformer tube material (T_{max} in Figure 2) places a limit on the furnace temperature as (costly) tubes get damaged at temperatures above T_{max}. The tube wall temperature (TWT) distribution further limits the average furnace temperature as shown in Figure 2, where the initial distribution has large temperature non-uniformity and hence, lower T_{avg}. However, reduction in the TWT non-uniformity, also called furnace balancing, allows for increasing the average furnace temperature through additional total fuel input, without violating the T_{max} constraint. Thus, furnace balancing becomes the means towards higher overall plant efficiency.

Process Data to Manufacturing Intelligence

The first step towards smart manufacturing is to gain greater insight into the process by placing appropriate sensors. While this requirement may seem obvious, it can be neglected. Instead, heuristics-based operations with minimal sensor-based support are common in the manufacturing sector. This can be attributed to the tenuous process of providing economic justification for acquiring the additional sensors or to the very lack of appropriate sensing technology. While the later scenario has to be tackled by promoting advanced research in sensing technology, the former can often be dealt through a sensor value-addition analysis within the SM framework.

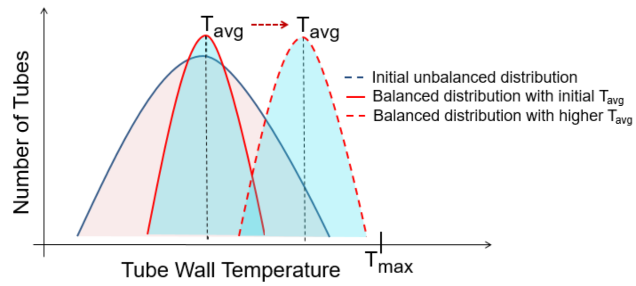

Figure 2. Furnace balancing [The temperatures are measured at a particular height for all the tubes.]

For the SMR test-bed, both of the hurdles came forth as the high temperature environment makes temperature measurements difficult. Common practice involves placing thermocouples on only a few tubes (due to economic constraints); the resulting -limited - information is insufficient for furnace balancing. Consequently, industrial practitioners rely on separately optimizing the tube-side (e.g., by monitoring the steam-carbon ratio) and the flue-gas side of the furnace (e.g., by monitoring the oxygen content of the exhaust gas). Digressing from the convention, in this study an array of state-of-the-art infrared cameras was installed around the furnace giving unprecedented continuous stream of TWT measurements (Kumar et al., 2016a).

The next step in SM is to convert the sensor data into manufacturing intelligence (MI), revealing new useful relationships between the process variables and enabling proactive decisions in dynamic environments. Although the use of process models is not a new concept, the extraction of knowledge from data historians through advanced data mining is still limited, due amongst others to lack of adequate data-management infrastructure. For the SMR, the infrared cameras allowed detailed investigation of TWT distribution relationship with the fuel distribution among the burners (which, in turn, is manipulated through fuel valves) through an extensive set of experiments performed on the furnace. An empirical SMR furnace model (Kumar et al., 2016a) was developed that allows in-situ measurement-noise filtering during model parameter estimation of an exponential response surface (Eq. (1)). In Eq. (1), ΔT_{ij} is the change in TWT of the i^{th} tube when the j^{th} burner fuel valve is closed by 1 degree, and a_j, ϕ_{xi}, ϕ_{yi} are the model parameters.

$$\Delta T_{ij} = a_j \exp(-\phi_{xi} x_{ij}^2 - \phi_{yi} y_{ij}^2) \qquad (1)$$

Data-driven models can also be complemented with high-fidelity models, e.g. CFD models, to generate model predictions with greater accuracy. Incorporating these high-fidelity models, however, often requires high performance computing (HPC) resources to enable business decisions in reasonable time. Unfortunately, HPC is still out of reach of many manufacturers due to the high investment cost of setting-up a HPC infrastructure or the lack of expertise in launching an analysis workflow (comprising multiple software) on a cloud- based HPC tool. Figure 3 shows the workflow deployed for furnace balancing. The MATLAB-based ‘Optimizer’ computes the required adjustments in the valve positions using the SMR model and the ANSYS Fluent-based CFD model verifies the recommendations before final implementations. Complete details can be found in Kumar et al. (2015). The SM platform, described later, facilitated the assembly and deployment of the workflow by providing an easy access to the HPC resources and easy-to-use workflow service.

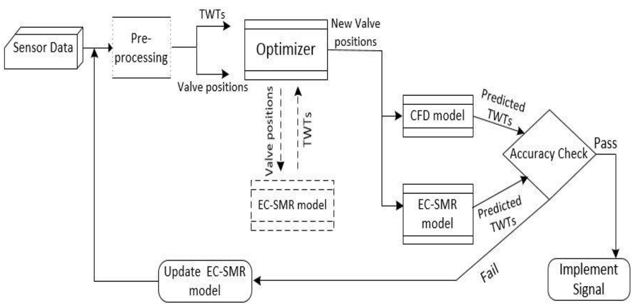

Figure 3. Workflow for furnace balancing

Enterprise-wide Agility

Manufacturing intelligence within SM is not restricted to factory premises and instead focuses on an integrated operations management across all the layers of the supply chain (depicted in Figure 4). Coordination of decision-making in real-time across the verticals of a manufacturing chain improves the material and asset utilization and thereby improves the process economics and the response to supply and demand variability. Studies on realization of agile enterprise-wide operations have started getting attention only recently (Baldea and Harjunkoski, 2014) where the production trajectories of the process units are continuously regulated optimally under exogenous influences such as variations in product demands or electricity prices (Pattison et al., 2016). Availability of comprehensive enterprise-wide data model along with forecast model for the exogenous factors becomes a prerequisite for successful MI implementation. These integrated models, however, are not yet a common feature in manufacturing enterprises.

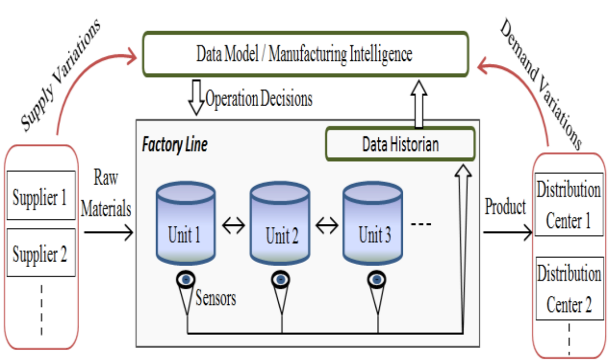

Figure 4. Layers of a manufacturing line

For the H_2 plant, changes in customer demand necessitates changes in SMR H_2 production which is effected by adjusting the natural gas process feed. Such an adjustment affects the TWT distribution as well, which, as described before, impacts the overall plant efficiency. Figure 5 shows the observed TWT distributions for three different feed rates; each distribution requires different valve adjustments for balancing the furnace. Note that the fuel valves in an SMR are not usually under automatic actuation and thus in the current scheme, furnace balancing is executed manually by the plant operators. To close the loop, a potential fully automatic furnace balancing solution was devised (Kumar at al., (2016b) by determining the optimal placement of (reduced number of) temperature sensors and valve actuators. They concluded that only about ten percent of the TWTs need to be measured to realise most of the benefits of furnace balancing. Thus, if the process feed is put under closed loop, the automatic furnace balancing solution can keep the furnace at its optimum efficiency by regulating the fuel distribution in real-time.

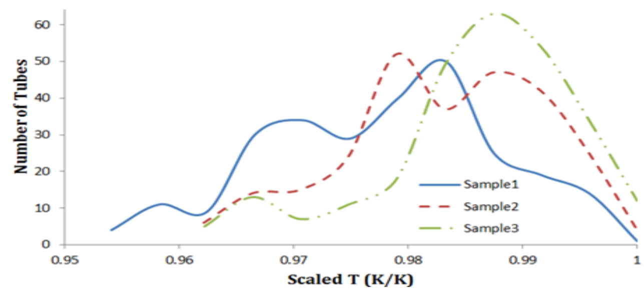

Figure 5. Impact of production variations on TWTs

Visualization-assisted Real-time Knowledge

Another important aspect of SM is to present the data in the form that it is most useful. Visualization and interpretation of data further immerses plant personnel in the decision-making process. Data visualization can assist in process analysis, e.g., through virtual-reality for troubleshooting collaboratively (Zhou, 2011) or through multidimensional diagrams for fault detection (Wang et. al., 2015), or it can be used for keeping the plant personnel motivated by providing continuous plant performance feedback. To provide real-time plant performance metrics, these visual modules need to be interfaced to the data historian and MI modules. As of yet, such visual modules are not readily available in one place in ready-to-use forms. Figure 6 shows the operator dashboard deployed for the SMR testbed. It shows the current TWTs and the predicted optimal distribution along with the required valve adjustments upon SMR model-based furnace balancing and is automatically updated at regular intervals. Note that actual numeric values have not been shown for proprietary reasons.

Smart Manufacturing Platform (SMP)

The aforementioned aspects of SM are also frequently mentioned in the context of IIoT (industrial internet of things), Industry 4.0, and digital factory but the SM platform-based approach distinguishes SM. The SMP is a

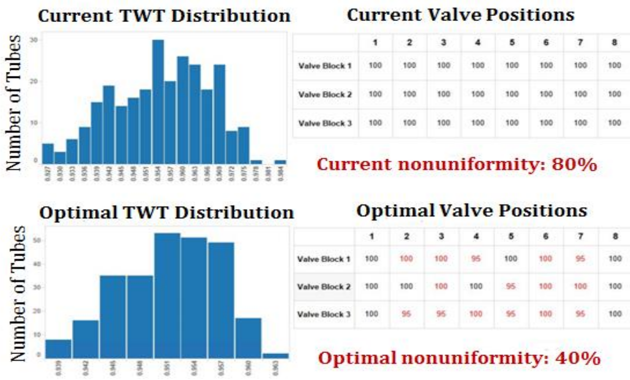

Figure 6. Operator dashboard for furnace balancing

cloud-based IT infrastructure that provides an easy access to the automation tools (see Figure 7) under one umbrella and thus acts as the enabler for overcoming the aforementioned limitations in adopting the best practices of SM (Davis et. al., 2015). Cloud infrastructure is attractive from a manufacturer's viewpoint due to the provision of low-cost scalable computing resources and the advantage of collaborating with third-party experts by connecting them with plant data securely outside of plant premises. Figure 7 also shows an instance of furnace balancing resulting in 44% reduction in TWT non-uniformity.

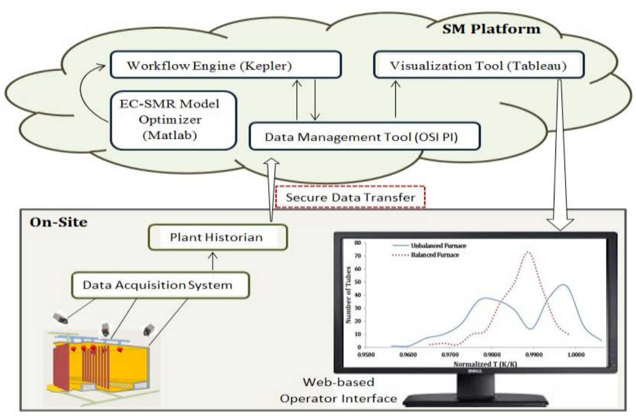

Figure 7. Integration of on-site and platform facilities (Terms in brackets refer to the respective software)

Another distinguishing feature of SMP is community-driven industrial 'app' marketplace (see Figure 8) analogous to smartphone Apps stores. Here, several customizable industrial process solutions (process, control, optimization models) in the form of standardized Apps are provided by App vendors. Manufacturing users can use these standalone Apps or combine them to form and execute composite workflows, e.g., furnace balancing solution. Data-driven models like the SMR model can be easily customized for a general furnace. Since the 'right' models are readily available on a pay-per-use basis, it cuts down the development cost and time, and thus allows low-cost deployment in a quick time.

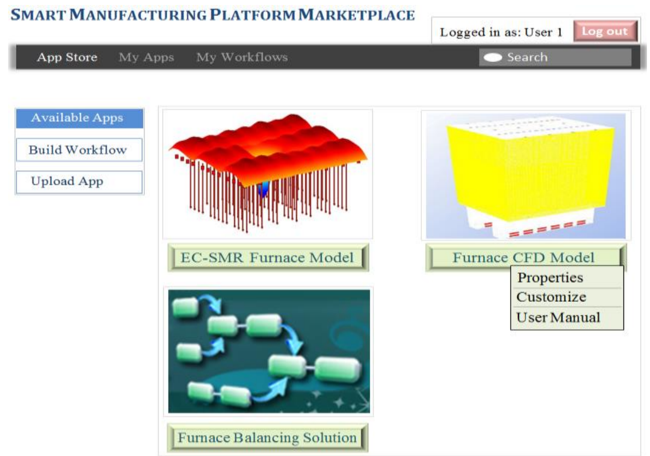

Figure 8. Representative schematic of SMP marketplace

Conclusions

In this work, a unified SM framework was presented using a H_2 manufacturing plant as an industrial application example. Availability of a centralized repository on the SMP encourages adoption of standardized manufacturing practices at different plants across the globe operated by an enterprise as well as sharing of best MI tools among the manufacturing community.

References

Baldea, M., Harjunkoski, I. (2014). Integrated production scheduling and process control: A systematic review. *Comput Chem Eng*, *71*, 377-390

Davis, J., Edgar T. F., Graybill, R., Korambath, P., Schott, B., Swink, D., Wang, J., Wetzel, J. (2015). Smart Manufacturing. *Annual Review of Chemical and Biomolecular Engineering*, 6, 141.

Kumar, A., Baldea, M., Edgar, T. F. (2016a). Real-time optimization of an industrial steam-methane reformer under distributed sensing. *Control Engineering practice*, 54, 140-153.

Kumar, A., Baldea, M., Edgar, T. F. (2016b). On optimal sensing and actuation design for an industrial scale steam methane reformer furnace. *AIChE J.*, doi:10.1002/aic.15333

Kumar, A., Baldea, M., Edgar, T. F., Ezekoye, O. A. (2015). Smart manufacturing approach for efficient operation of industrial steam-methane reformers. *Industrial & Engineering Chemistry Research*, 54 (16), 4360-4370.

Pattison, R.C., Touretzky, C.R., Johansson, T., Harjunkoski, I., Baldea, M. (2016). Optimal Process Operations in Fast-Changing Electricity Markets: Framework for Scheduling with Low-Order Dynamic Models and an Air Separation Application. *Industrial & Engineering Chemistry Research*, *55*(16), pp.4562-4584.

Smart Manufacturing Leadership Council (SMLC). (2011). Implementing 21st century smart manufacturing. W*orkshop summary report*, SMLC and U.S. DOE.

Wang, R.C., Edgar, T.F., Baldea, M., Nixon, M., Wojsznis, W., Dunia, R. (2015). Process fault detection using time-explicit Kiviat diagrams. *AIChE Journal*, *61*(12), pp.4277-4293.

Zhou, C. Q. (2011). Visualizing the Future in Steel Manufacturing. *Iron & Steel Technology, 8(1), 37-50.*