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DIGITAL TECHNOLOGIES

Utilize a process simulation digital twin to optimize condensate yield

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ADNOC Sour Gas (ASG) is one of the Abu Dhabi National Oil Companies' (ADNOC) gas producers with the capacity to produce 1.45 Bft^{3}d of sour gas.

ASG is a joint venture (JV) between ADNOC (60%) and Occidental Petroleum (OXY), which owns a 40% share. It was established in 2010 to maximize the value of the Shah Gas Field. Since then, it has built a reputation as a reliable supplier of gas and one of the world's leading sulfur producers.

With the aim to maximize profit, and contribute to sustainability targets by reducing greenhouse gas (GHG) emissions, ASG has optimized condensate hydrotreater operation by adjusting Reid vapor pressure (RVP), which resulted in maximizing condensate yield.

Shah hydrocarbon condensate is processed through condensate stabilizers, and then from hydrotreaters, before finally routing to condensate storage tanks. The accurate measurement and prediction of condensate product vapor pressure are important for safe storage and transportation to minimize vaporization losses and for environmental protection. The maximum true vapor pressure (TVP) for floating roof tanks is ~14.7 psi, whereas the design range for Shah stabilization and hydrotreating units is 4 psi–8 psi.

At the time of commissioning of the unit discussed in this study, the condensate yield was maximized by operating the plant at an acceptable higher RVP, while maintaining the export condensate temperature vs. RVP limit. However, it was estimated that additional margin will become available with further optimization of operating conditions at the stabilizers and the hydrotreater stripper. This optimization demanded the development of a smart digital twin to visualize dynamic TVP for export condensate at operating conditions. An in-house study has been conducted to optimize hydrotreater operation to maximize condensate production, utilizing the available design margin by using a hybrid process simulation enabled with artificial intelligence (AI) capabilities.[a]

In Phase 1 of the study, a manual table was generated using a first principles-based process simulation[b] to identify the TVP at different RVPs and condensate product temperature values.

In Phase 2, a data-enabled simulation model was created with a calculated TVP soft tag. The model was linked with actual plant operating data through an available historian platform and published on a web-based graphical interface[c] for greater visualization. The AI and first principles-enabled hybrid model[b] application was used to predict TVP accurately and dynamically at plant running conditions. The hybrid model helped with the monitoring of TVP at varying condensate product temperatures and RVPs. This allowed plant personnel to adjust key parameters (e.g., column trays temperature controller) to maximize condensate yield.

This initiative and the operating approach resulted in many benefits, including enhanced condensate yield while monitoring TVP based on actual operating conditions. This led to incremental revenue and a reduction in vapor load on the vapor recovery compressor, thus saving power, reducing medium-pressure (MP) steam load and reducing GHG emissions.

Condensate hydrotreater process description. The condensate stabilization section is designed to remove water, hydrogen sulfide (H_2S), light mercaptans and light hydrocarbons from liquids recovered in the slug catcher and the feed gas separation section. The condensate stabilizer overhead is air cooled in the stabilizer reflux condenser and fed into the stabilizer reflux drum.

The lean gas from the stabilizer reflux drum is sent to the vapor recovery compressor first-stage suction drum. The condensate stabilizer bottom tray liquid is heated in the stabilizer reboiler, which utilizes MP steam. Stabilized condensate leaves the bottom of the condensate stabilizer column and is cooled first by the stabilizer side reboiler and then by the stabilizer feed preheater. The stabilized condensate then flows to the condensate hydrotreating unit, under level control.

In the stripper, residual light ends, H_2S and hydrogen (H_2) are stripped from the condensate to meet the H_2S specification of < 10 ppmw in the bottoms product. To reduce the heat load on the H_2S stripper reboiler, the column is provided with a H_2S stripper side reboiler that exchanges heat between a draw-off stream from a chimney tray above Tray 21 and the column bottoms product. The overhead from the condensate H_2S stripper flows on pressure control to the vapor recovery system.

The H_2S stripper bottom tray liquid is heated by the H_2S stripper reboiler, which utilizes saturated MP steam as the heating medium. The stabilized hydrocarbon condensate leaving the bottom of the condensate H_2S stripper is cooled in the H_2S stripper side reboiler and product cooler before being sent to storage. Off-spec condensate is redirected to the blowdown drum (**FIG. 1**).

Using a hybrid model, an in-house study was conducted to optimize the hydrotreater operation to maximize condensate production utilizing the available design margin.

Scope. This article summarizes the condensate maximization initiative outcomes of Phase 2. In Phase 1, a manual RVP/TVP matrix was generated and used to calculate the operating TVP. In Phase 2, a process simulation digital twin was developed using a hybrid model. A soft sensor of the TVP was created for direct monitoring of condensate export TVP at actual operating conditions.

BOUNDARY CONDITIONS OF THE RVP TEST RUN

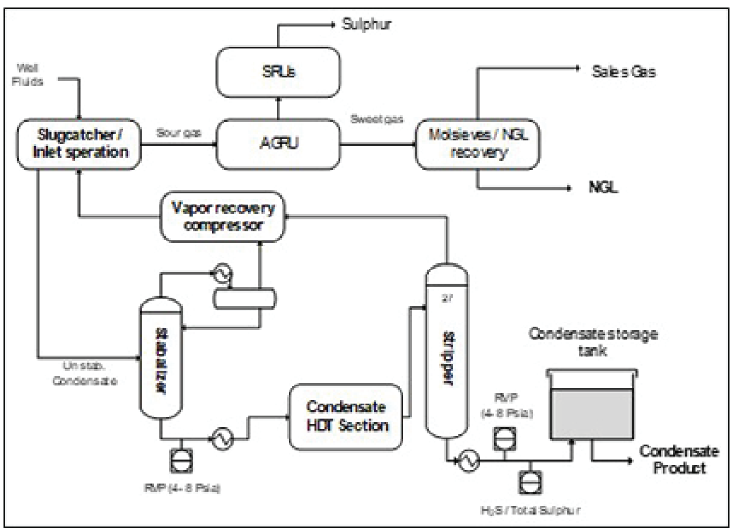

FIG. 1. Shah HC condensate processing schematic.

Boundary conditions. An internal study was conducted to identify the effect of increased RVP on condensate yield using first principles-based process simulation. A generated matrix and guidelines have been provided to identify the maximum safe limit of operating the TVP for both Summer and Winter Cases (**TABLE 1**). It was concluded that by increasing the RVP by 0.5 psi, the condensate yield increases by 1%, equivalent to 166 bpd. Therefore, it is recommended to operate the RVP for each case as: Summer Case (5.5 psi–6.5 psi) and Winter Case (7 psi–8 psi).

Condensate yield increase test run. In November 2021, a test run was conducted to increase condensate yield as per the provided TVP matrix to keep condensate product temperature and RVP within the green zone to ensure safe operation. The test run has been divided into two phases to increase RVP in both the stabilizer and stripper sections (**TABLE 2**).

TABLE 1. RVP vs. TVP at condensate temperature simulation results—(green zone) recommended for continuous operation; (yellow zone) not recommended for continuous operation; and (orange zone) operation to be avoided

RVP at 38°C, psia	TVP at 38°C, psia	TVP at 45°C, psia	TVP at 50°C, psia	TVP at 55°C, psia	TVP at 60°C, psia
5	5.4	6.9	8.1	9	10.5
5.5	6.4	7.7	8.9	10.3	11.7
6	7.2	8.8	9.9	11.3	12.8
6.5	8	9.6	10.9	12.4	13.9
7	8.9	10.6	12	13.5	
7.5	9.6	11.5	12.8	14.4	
8	10.5	12.4	13.8		

TABLE 2. RVP test run basis		
Test run stages	**From**	**To**
Phase 1	5.4 psi	6 psi
Phase 2	6 psi	6.5 psi

TABLE 3. RVP test run results

Test run	Feed gas, MMft³d	Condensate product, bpd	CGR, bpd/MMft³d	Condensate yield increase, bpd	RVP (PHD), psi	RVP (Lab), psi	Steam, tph
Difference (November–December) results	1,280	675	0.49	632.4	0.7	0.8	4.1

TABLE 3 summarizes the outcome of the RVP test run, where an extra ~630 bpd of condensate yield were achieved with a condensate-to-gas ratio of 0.49, considering an increase of 1 psi RVP in all stabilizer and stripper sections. **TABLE 3** values have been projected with an average increase of 1 RVP throughout the year. An extra increase of ~300 bpd could be gained with an increase of RVP to 6.5 psi. The total steam savings is around 4 tph.

CONDENSATE YIELD OPTIMIZER TECHNOLOGY

Machine-learning background. Machine-learning has emerged as a powerful tool across various industries, revolutionizing decision-making and predictive capabilities. In the oil and gas sector, where vast amounts of data is generated daily, harnessing machine-learning can lead to enhanced efficiency, safety and profitability. To successfully implement machine-learning solutions, a structured approach involving key steps is crucial. The following sections discuss the intricacies of each step, highlighting their significance and challenges.

Get the data: The foundation of any successful machine-learning endeavor is quality data. In the oil and gas industry, data is derived from sensors, logs and historical records, among others. Gathering relevant, accurate and diverse data is the initial step. This involves identifying the sources, extracting raw data and preparing it for analysis. Challenges may arise in data availability, compatibility and consistency, requiring careful curation.

Define key performance indicators (KPIs): Clear objectives are essential for effective machine-learning. Defining KPI metrics to be predicted or optimized guides the entire process. In the oil and gas segment, KPIs can range from equipment failure prediction to reservoir performance optimization. A well-defined KPI aligns stakeholders, clarifies expectations and ensures the machine-learning solution addresses business needs.

Clean and recondition the data: Raw data often contains noise, outliers and missing values. Cleaning and reconditioning involve data preprocessing steps such as removing duplicates, inputting missing values and handling outliers. Data normalization and transformation ensure the data is suitable for the chosen algorithm. This step is pivotal, as inaccurate or unprocessed data can lead to misleading model results.

Choose the proper algorithm: Selecting the right algorithm depends on the problem type and data characteristics. In oil and gas applications, algorithms can range from regression and decision trees to neural networks and deep learning. Each algorithm has its strengths and limitations, and the choice should be driven by the nature of the KPI and data. Iterative experimentation with different algorithms may be necessary to find the optimal fit.

Validate the model: Model validation is critical to assess its performance and generalization ability. Splitting the data into training and testing sets allows the model's accuracy to be tested on unseen data. Cross-validation techniques further enhance reliability. Metrics such as accuracy, precision, recall and F1-score provide insights into the model's effectiveness. Overfitting or underfitting issues should be addressed through appropriate adjustments.

Deploy the model: Deploying the model for real-world use requires integration with existing systems. The deployment process involves transforming the model into a usable format, connecting to existing systems and data, and ensuring scalability and reliability. Continuous monitoring and periodic retraining are necessary to adapt to changing data patterns and ensure the model's longevity.

Each step in the machine-learning process presents its challenges and complexities. For instance, data collection can be hindered by data privacy and security concerns. Defining the right KPI requires a deep understanding of business goals. Cleaning data might require innovative techniques to handle unconventional data sources. Algorithm selection demands expertise in both domain knowledge and machine-learning. Model validation necessitates thorough analysis and interpretation of evaluation metrics. Deployment requires coordination between data scientists, information technology (IT) and operations teams.

The oil and gas industry has witnessed remarkable advancements through the implementation of machine-learning. Predictive maintenance has minimized downtime, optimizing production schedules; reservoir modeling using machine-learning has improved oil recovery estimates; and real-time data analytics have enhanced safety and operational efficiency.

AI solution. To enhance the predictability of RVP/TVP values and ensure the safe and efficient operation of processes, the authors' companies have implemented cutting-edge technology. This workflow solution[a] is designed to dynamically predict TVP accurately under actual plant operating conditions, creating a soft tag for TVP that facilitates monitoring at the condensate product's real temperature and allowing for parameter adjustments.

The hybrid model combines the AI and first-principles knowledge to deliver comprehensive, accurate models more quickly without requiring specialized expertise. In this approach, an existing first-principles model is augmented with an AI-driven solution that uses data from operations to improve the model accuracy and predictability. The hybrid models are commonly used to provide performance parameters that are not predicted by first principles alone. Machine-learning is used to determine the unknown relationships between those parameters and key process variables to continuously calibrate the model as process conditions change.

The core functionality of this application lies in training a sophisticated machine-learning model to define dependent variables and construct a soft sensor for predicting RVP. This is achieved by providing the model with a set of independent variables that are influenced by changes in RVP. These variables include (but are not limited to) condensate feed temperature, condensate flow, stripper tray temperature, reboilers steam flow, RVP, condensate product flow and the constraints associated with each parameter.

The model undergoes an extensive training process, simulating various scenarios to learn and predict these variables across a wide temperature setpoint range. The resulting machine-learning model is then seamlessly integrated into a first principles-based process simulation, providing highly accurate predictions (**FIG. 2**).

Methodology. To transform the machine-learning model into a visually intuitive dashboard suitable for operational TVP monitoring, a systematic process was undertaken. This involved fine-tuning the existing machine-learning model while effectively linking it with historical data.

Subsequently, soft tags were meticulously developed and configured to provide estimations for both TVP and RVP. To ensure seamless integration, the dashboard's design structure was collaboratively created in conjunction with the IT team (**FIGS. 3** and **4**).

To guarantee its effectiveness and reliability, the dashboard underwent a comprehensive conversion process from an offline configuration to an online environment. Rigorous testing was conducted to validate its functionality and accuracy before it was made accessible for operational use.

Process evaluation. TABLE 4 and **FIG. 5** summarize the incremental production of maximizing condensate due to the increased RVP from October 2022–mid-December 2022, where an extra ~630 bpd of condensate yield were achieved with a condensate-to-

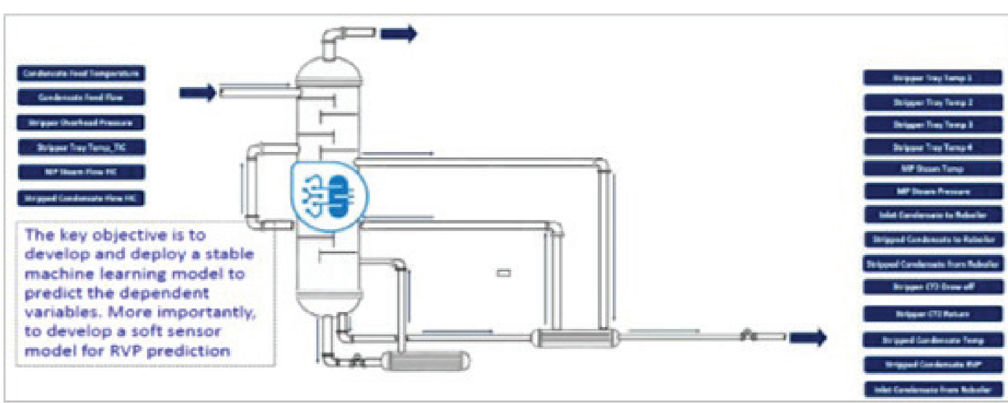

FIG. 2. Hybrid model for H_2S stripper.

gas ratio of 0.49, considering an increase of 1 psi RVP as per lab analysis in both the stabilizer and stripper sections. The projected values reported in **TABLE 4** are based on an average increase of 1 RVP across the year. The total steam savings is ~1 tph.

Takeaways and prospects. The implementation of the condensate yield optimization dashboard has resulted in significant advantages, including:

- **Real-time TVP monitoring:** Providing operations and the process team with a visual representation of TVP under actual operating conditions.

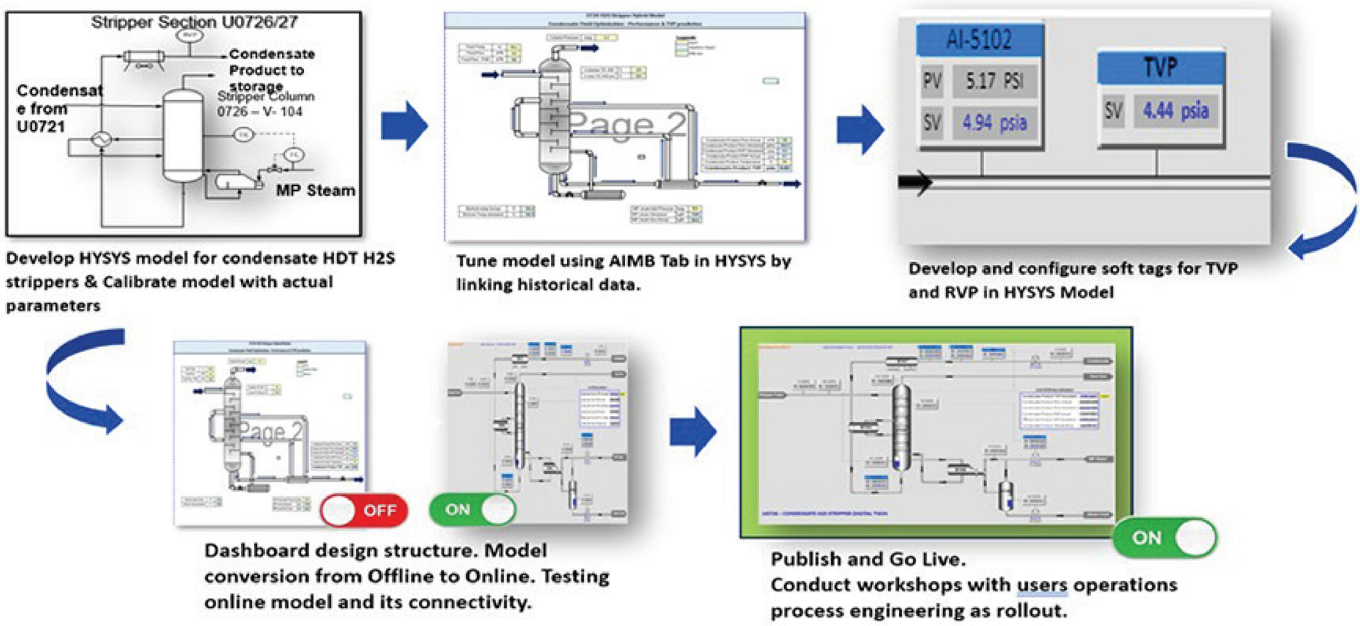

FIG. 3. Implementation steps: AI-augmented digital twin.

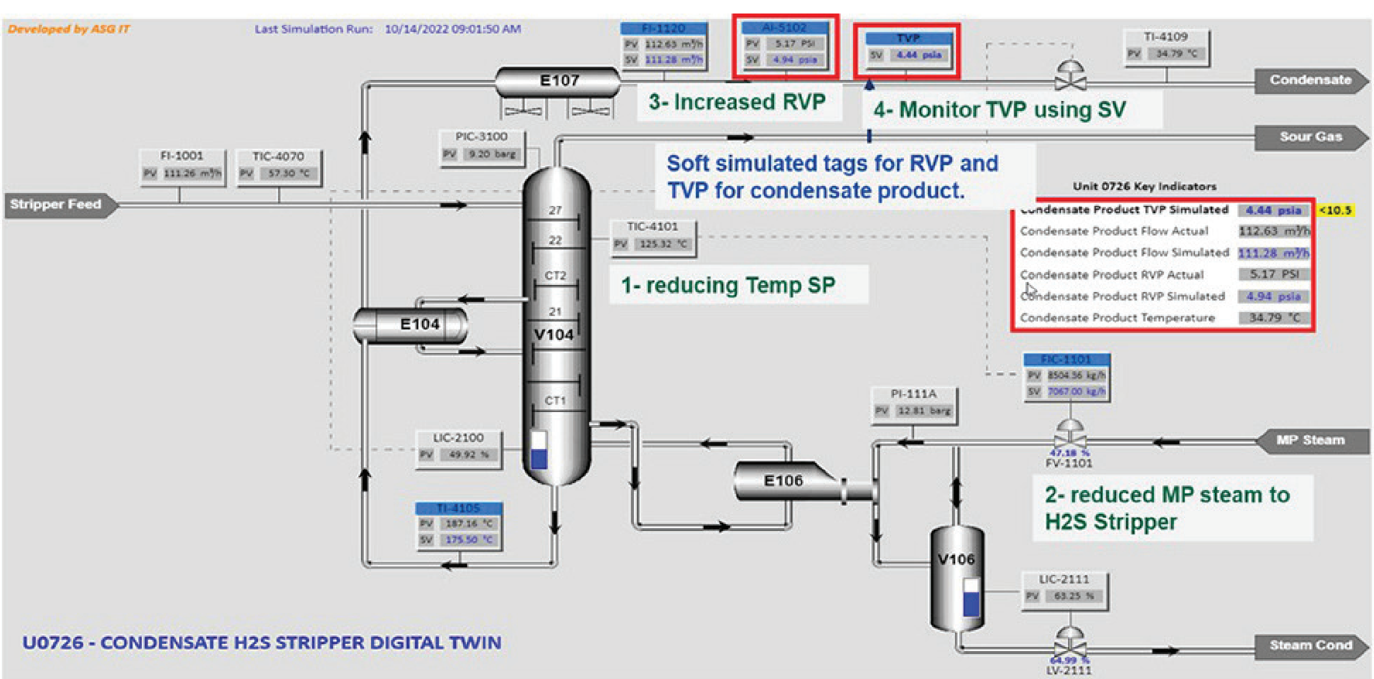

FIG. 4. Visualization dashboard.

TABLE 4. Production results with increased RVP

Test Run	Feed gas, MMft^{3}d	Condensate product, increased difference, bpd	CGR, bpd/MMft^{3}d	Condensate yield increase, bpd	RVP (PHD), psi	RVP (lab), psi	Steam, tph
Difference	1,291	684	0.49	630	0.4	0.9	1.1

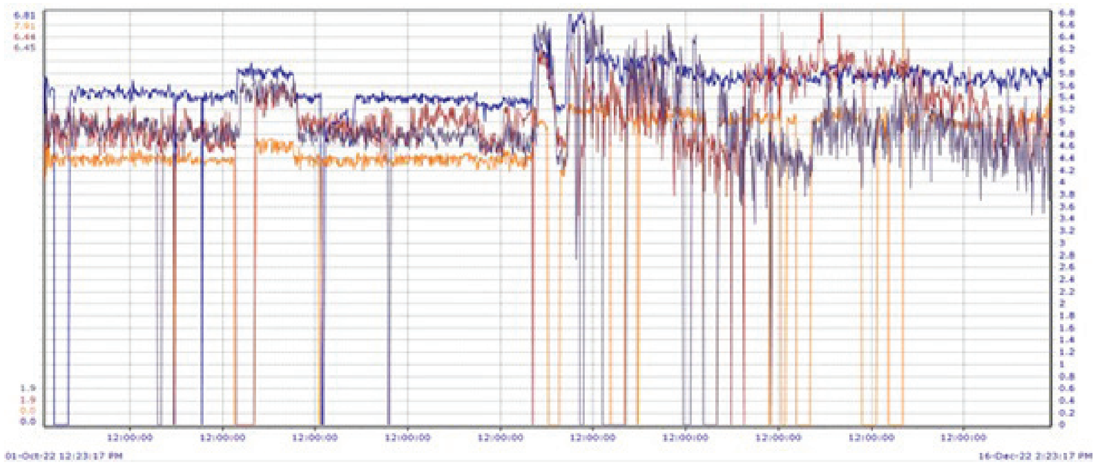

FIG. 5. U0721/22–U0726/27 stabilizers and strippers RVP trend from October–December 2022.

- **Enhanced condensate yield:** The ability to adjust stabilizer and stripper parameters to maximize condensate yield while closely monitoring TVP.
- **Environmental benefits:** Reduced medium-pressure steam load resulting in decreased GHG emissions.
- **Energy savings:** A decrease in vapor load on the vapor recovery compressor, translating into power savings.
- **Profitability guidance:** The integration of TVP/RVP simulated soft tags for informed decision-making and more profitable operation.
- **Performance evaluation:** Real-time assessment of unit performance via the process digital twin.
- **Predictive column performance:** Integration of machine-learning models with first principles-based process simulation for predicting column performance over a wide temperature range.
- **Analyzer redundancy:** Availability of RVP soft analyzers when online analyzers are unavailable.

Moving forward, the condensate yield optimization dashboard stands as a testament to the potential gains offered by advanced technology, emphasizing the importance of real-time monitoring, data-driven decision-making and sustainability. Continuous improvements and refinements to the system will ensure that these benefits are maximized while contributing to the overarching goals of efficiency and environmental responsibility.

The future normal operation of stabilizers and strippers should be updated to maximize the condensate yield by maximizing RVP while using the RVP-TVP estimation dashboard, limiting TVP for condensate export to 10 bar.

During the maintenance of RVP analyses, soft simulated TVP and RVP can be used for product quality monitoring purposes. HP

NOTES

a. Aspen Hybrid Models™ and Aspen AI Model Builder™
b. Aspen HYSYS®
c. aspenONE® Process Explorer™

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