Smart Control and Instrumentation Strategies for Optimizing Gasification Processes in Saudi Arabia's Integrated Energy Facilities.

Abstract

Gasification is a strategically important method of conversion for integrated energy facilities since it connects heterogeneous carbon-based feedstocks with dispatchable synthesis gas, power, steam, hydrogen and downstream chemical production. Its industrial value, though, relies on keeping within a narrow range of operation even though the reaction kinetics are nonlinear, the measurement conditions are severe, the characteristics of the feed vary and there are strong interactions between oxygen, steam, solids circulation, temperature, pressure and syngas composition. This review brings together the literature published between 2020 and 2025 on smart instrumentation, status evaluation, advanced control, machine learning and digital twins for gasification and then converts the findings as a framework for implementation in Saudi Arabia. A structured, PRISMA-informed integrative review was carried out, with the evidence assessed for methodological clarity, the quality of validation, its relevance to real-time control and its transferability to integrated energy facilities. The synthesis reveals a clear trend moving from conventional regulatory loops towards sensor fusion, Kalman filtering, model predictive control, neural-network-assisted prediction, explainable machine learning and bidirectional digital-twin architectures. Recent pilot-scale studies have shown that constrained model predictive control can regulate the coupled gasification variables, state prediction can recover the poorly measured internal states and online spectroscopy can improve the monitoring of syngas and tar. For Saudi facilities, especially those of the Jazan type – that is, gasification-power-steam-hydrogen complexes – the most valuable architecture is a layered system which maintains safety-certified basic control while also incorporating validated soft sensors, supervisory predictive control, equipment-health analytics and plantwide economic optimisation. The review points out ongoing gaps in industrial-scale validation, sensor fouling compensation, uncertainty measurement, cybersecurity and cross-unit coordination. A phased roadmap is suggested in order to enhance availability, syngas consistency, hydrogen quality, energy efficiency and carbon performance without losing process safety.

1. Introduction

Gasification involves reacting solid or liquid carbon-containing materials with oxygen, steam, carbon dioxide, or mixtures of these to produce a combustible synthesis gas. The resulting stream is mainly made up of carbon monoxide and hydrogen, while the amounts of carbon dioxide, methane, water, sulphur compounds, particulates, tars and various trace impurities depend on the type of feedstock and the design of the reactor. Recent reviews have indicated that the reactor configuration, the gasifying medium, the equivalence ratio, temperature, pressure, residence time and the composition of the feed have a strong effect on carbon conversion, heating value, tar formation and hydrogen yield [18-21]. Because of these interactions gasification is suitable for use in integrated energy systems, but the process is also difficult to operate close to optimal conditions when using separate single-loop controllers. A disturbance that manifests itself locally as a change in feed flow can affect the heat release, the behaviour of the slag, the composition of the syngas, the loading on downstream cleaning processes and finally the performance of the power, hydrogen or chemical-production units.

The limitation of measurement techniques leads to an increase in control difficulty. Since industrial gasifiers function under high temperature, pressure, and solids loading, it is not possible to measure many of the chemically significant states directly at the necessary frequency. Thermocouples give only local temperature data; pressure taps and differential-pressure transmitters are prone to fouling; the flow of solids and the moisture content of the feed are uncertain; and extractive gas analyzers cause a transport delay. The raw gas, which contains tar, sulfur, and particulates, can also contaminate the sampling systems. For these reasons, experimental studies have shifted to the use of heated optical cells, robust spectroscopy, inferential measurements, and state estimators that combine a limited number of sensors with process models [1,22-24]. Valipour et al. demonstrated that Kalman-filter-based estimation could reconstruct most of the internal states of a large reduced-order entrained-flow gasifier model even when online temperature sensing was limited [1]. These results are important since advanced control is only as reliable as the state information provided to it.

The literature on control has at the same time shifted from set-point regulation to prediction and optimization. Dynamic recurrent neural networks have been applied in order to represent the behaviour of a pilot-scale entrained-flow gasifier when carrying out constrained optimization amidst load-following and co-firing conditions [2]. The use based on data-driven identification together with model predictive control has shown high forecast precision and the capability of adjusting the equivalence ratio in order to regulate the outputs from biomass gasification [3]. More recently, hierarchical model predictive control has been tested experimentally on a 100 kW dual-fluidized-bed plant, and neural-network MPC has combined long short-term memory prediction with real-time optimization for the purpose of temperature control [4,5]. Digital-twin studies have extended this approach by continuously synchronising physical measurements, physics-based models, data-driven surrogates, soft sensors and optimization functions [6,7].

Saudi Arabia offers a particular kind of application situation. The Jazan Integrated Gasification and Power Company has assets linked to an integrated gasification combined-cycle facility, air separation and utilities; Aramco stated that the joint venture generates power, steam, hydrogen and other utilities through a long-term operating agreement [28]. Moreover, Vision 2030 stresses industrial transformation, energy efficiency, localization, digitalization and a more diversified energy economy [29]. Given these priorities, there is a strong basis for adopting gasification control strategies which do not simply optimize reactor temperature or gas composition, but rather the performance of the whole interconnected utility system. The practical research question then becomes how the latest smart sensing and control methods can be combined into an industrially viable architecture appropriate for Saudi integrated energy facilities.

2. Aim, Objectives and Review Contributions

This review intends to combine the evidence from 2020 to 2025 regarding intelligent sensing, system estimation, advanced process control and digital-twin-enabled optimisation for gasification, and then convert that evidence into a control structure which is specific to Saudi conditions for integrated power, steam, hydrogen and syngas facilities.

First of all, the review identifies the main controlled variables, the manipulated variables, the disturbances and the measurement restrictions which affect gasifier stability and product quality.

Second, it compares conventional regulatory control, Kalman-filter state assessment, model predictive control, neural-network-assisted control, explainable machine learning and digital twins on the basis of their strengths, limitations and degree of implementation maturity.

Thirdly, it looks at the way online analyzers, soft sensors and the various data-quality functions can reduce uncertainty regarding the composition of syngas, the temperature fields, the tar loading and other difficult-to-measure quantities.

Fourth, it adjusts the technology evidence to suit the Saudi integrated facilities, since gasification has to co-ordinate with the supply of oxygen, syngas cleanup, hydrogen production, the steam networks, combined-cycle generation and the carbon-management objectives.

Fifth, it suggests a step-by-step roadmap for research and deployment that regards process safety, cybersecurity, operator trust, model governance and economic performance as equally important design requirements.

3. Review Methodology

An integrative review based on a formal approach was chosen since the evidence base comprises experimental control studies, process-modeling papers, machine-learning studies, instrumentation research, review articles and official Saudi project or policy documents. A statistical meta-analysis would not be suitable since the various systems differ greatly in terms of reactor type, scale, feedstock, response variable, controller structure and validation method. The protocol for the review was guided by the PRISMA 2020 principles concerning transparent identification, screening and reporting [26,27,30], even though the synthesis was adapted to the needs of process-systems engineering rather than to clinical evidence.

The time frame for the literature review was from January 2020 to December 2025. The search terms were divided into four categories: gasification technology; sensing and instrumentation; control and optimization; and relevance to Saudi integrated energy. Examples of representative combinations were "gasification AND model predictive control", "entrained flow gasifier AND Kalman filter", "gasification AND soft sensor", "syngas AND online spectroscopy", "gasification AND machine learning", "gasification AND digital twin", and "Saudi Arabia AND gasification

AND integrated energy". The search structure used was based on title, abstract and keyword logic suitable for Scopus and the Web of Science, and during source verification the publisher's records and DOI metadata were checked. This is in line with the transparent multi-database search approach used in recent systematic engineering reviews, in which the keyword blocks, the year filters and the inclusion criteria are explicitly stated.

A study was included only if it was published in English between 2020 and 2025 and had made a direct contribution to at least one of the following areas: gasifier dynamics; real-time sensing; state assessment; process monitoring; predictive control; machine-learning prediction; digital-twin architecture; optimization; or the deployment of gasification in Saudi Arabia. Preference was given to peer-reviewed journal articles. Two of the official sources were kept since the Saudi application necessitates primary evidence about the structure of the Jazan asset and the national transformation context [25,28,29]. Exclusion from the study was applied when the work dealt solely with equilibrium chemistry and had no operational relevance, provided no identifiable basis for validation, was a duplicate of another record, or was outside the publication time frame. Thirty sources were included in the final manuscript..

The quality appraisal employed five areas: objective clarity, the appropriateness of the method, the strength of validation, reproducibility, and the degree of transferability to real-time operation. Within each area, a score was given on a scale from zero to two, and evidence covering at least seven out of ten cases was considered to represent high confidence. When it came to making claims about deployment, studies from a pilot or industrial setting were given greater weight, and reviews were used to identify technology families while official sources provided the Saudi-specific context.

The data extraction included information on the reactor type, the feedstock, the scale, the measured variables, the manipulated variables, the modelling approach, the controller or estimator, the validation mode, the performance claim and the identified limitation. Thematic synthesis was then used to classify the findings under the following categories: instrumentation, system estimation, regulatory control, MPC, AI-enabled prediction, digital twins, plantwide optimization and deployment governance. Where possible, the claims were triangulated using multiple kinds of sources. No numerical performance value wasexceededd the conditions stated in the source original source. This point is important since high prediction accuracy for a laboratory dataset does not prove closed-loop robustness if sensor drift, feed changes, equipment degradation or safety requirements are taken into account.

4. Process Variables, Instrumentation and State Awareness

The main control issue is multivariable since the gasifier temperature influences the reaction speeds, carbon conversion, ash behaviour and tar formation, yet the temperature itself is affected by the amount of oxygen, the addition of steam, the feed rate, the heating value of the feed, the moisture content, mixing and heat loss. Pressure has an impact on residence time and on the need for downstream compression, and in fluidised systems bed differential pressure or indicators of solids circulation become important. The equivalence ratio is still one of the most significant operating variables in that increasing the oxidant can stabilise the conversion and raise the temperature, but too much oxidation uses up the combustible material and may lower the heating value of the syngas. Steam has an effect on both the thermal balance and the hydrogen-forming reactions. Reviews of biomass and catalytic co-gasification always point out temperature, equivalence ratio and feed blending as the key performance parameters [18-21].

In order to facilitate control, the process ought to be depicted as a hierarchy of variables not as a simple tag list. The fast protective measurements are pressure, differential pressure, oxygen flow, steam flow, fuel flow, valve position and the key temperatures. The quality measurements consist of H_2, CO, CO_2, CH_4, H_2S, water, particulate or tar indicators and the calculated heating value. The slow condition variables are refractory health, slag thickness, fouling, raw material composition and instrument drift. The rapid measurements support safety and regulatory loops; the quality analyzers assist with supervisory corrections; and the slow condition variables provide information for constraint adaptation and maintenance. The separation according to time scale stops a high-level optimizer from trying to make up for a failed transmitter or for a deteriorating refractory by operating the reactor more intensely.

Online measurement of composition is particularly useful since the quality of syngas acts as a link between the operation of the reactor and the downstream value. Pushp et al. showed that a heated FTIR setup can be used to monitor the spectral attributes of permanent gases, water, and tars while preventing condensation on the optical components [22]. Ojha et al. suggested a highly sensitive method for monitoring tars based on oxygen demand [23]. These methods show a general principle regarding instrumentation, namely that the analyzer interface must be designed for the process environment. Heated sample lines, automatic purge procedures, redundant validation, calibration tracking and sample-system diagnostics should be considered as part of the measurement system and not as separate auxiliary equipment.

When it is too slow or impossible to make direct measurements, soft sensors can deduce the states from the faster-measuring variables. State estimation process offers a method that is based on physical principles. In the entrained-flow study carried out by Valipour et al., Kalman filtering was examined under various sensor configurations, model mismatch, uncertainty in the prior estimate, and load-following conditions, and the estimator was able to recover a very large portion of the model states [1]. For the gasifiers in Saudi Arabia, a practical estimator could use the temperatures, the pressure, the ratio of oxidant to feed, the syngas flow and the analyzer data to estimate the unmeasured temperatures in the reaction zone, the carbon conversion, the slag condition or the composition over a short horizon. Estimation should be supported by confidence intervals or residual diagnostics; an optimizer has to know when an inferred state is unreliable.

Machine-learning soft sensors broaden the range of possible models. Wen et al. applied XGBoost in order to examine the importance of the gasification inputs [14], whereas reviews of ensemble models show good predictive performance as well as highlight concerns regarding explainability and overfitting [9,10]. More recently, transformer-based predictions of the composition of pilot-scale entrained-flow syngas have demonstrated that the oxygen-to-coal ratio is a highly influential factor and that explainability tools such as SHAP can reveal how the model behaves [11]. Industrial data from coal gasification have also been used in conjunction with automated model selection, SHAP interpretation and optimisation [12]. The results show that AI can serve as an advisory and inferential layer, but not as a complete replacement for safety-rated instrumentation.

Table 1. Critical gasification variables, instrumentation risks and smart measurement complements.

Process variable	**Primary instrument / signal**	**Principal measurement risk**	**Control or optimization use**	**Smart complement**
Gasifier temperature	Protected thermocouples; selected optical temperature sensing	Local bias, drift, radiation effects, slag or refractory exposure	Reaction stability; carbon conversion; slag behavior; tar suppression	Redundant validation; spatial state estimation
Pressure	Pressure transmitters and fast trip signals	Impulse-line plugging; calibration drift	Residence time; pressure stability; downstream compatibility	Residual diagnostics and voting
Bed / solids inventory	Differential-pressure transmitters; solids-circulation indicators	Erosion, plugging, density changes	Fluidization quality; circulation; heat transfer	Estimator using flow, ΔP and temperature
Feed rate and moisture	Weigh feeder / mass flow; feed characterizatio n	Heterogeneity, feeder slip, moisture variation	Energy balance; oxygen and steam ratios	Reconciled feed-quality soft sensor
O_2 and	Mass/volumetri	ASU	Equivalence	Constraint

Process variable	**Primary instrument / signal**	**Principal measurement risk**	**Control or optimization use**	**Smart complement**
steam delivery	c flow measurement with ratio stations	dynamics; valve stiction; flow bias	ratio; steam-to-carbon ratio; heat balance	monitor and actuator-health analytics
Syngas H_2, CO, CO_2, CH_4	GC / FTIR or other validated composition analyzer	Sampling delay, condensation, calibration and fouling	H_2/CO ratio; heating value; downstream quality	Fast composition soft sensor with analyzer reconciliation
H_2S, tar and particulates	Sulfur analyzer; heated spectroscopy; tar proxy / oxygen-demand sensing	Sample-system fouling; low-frequency reference tests	Cleanup loading; catalyst protection; emissions control	Analyzer-health model and confidence flag
Slag / refractory condition	Skin temperature, heat-flux trends, inspection data	Internal state inaccessible online	Constraint adaptation; asset life; outage planning	Kalman or hybrid state estimation

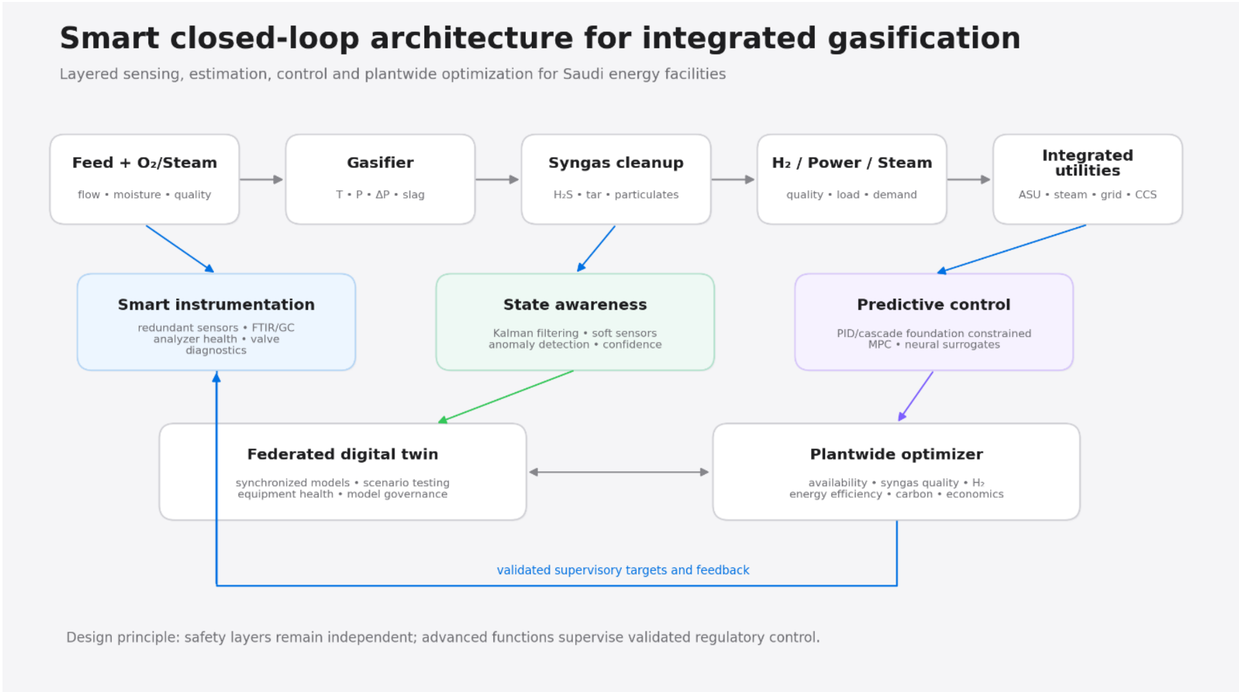

Figure 1. Smart closed-loop architecture for integrated gasification

5. Smart Control and Optimization Strategies

Traditional proportional-integral-derivative control is still the basis of industrial processes since it is transparent, quick to respond, and well understood. Devices such as flow controllers, pressure controllers, furnace draft loops, oxygen-to-feed ratio control stations, steam ratio controllers and temperature cascades offer definite protection against typical disturbances. The problem with them is not that they are outdated, but that a nonlinear gasifier has interacting constraints and delayed quality measurements which cannot be adequately managed by separate loops. For this reason a reasonable smart-control structure retains the regulatory loops at the level of the distributed-control system and includes higher levels which compute targets that are better from an economic or operational point of view.

Model predictive control is especially well suited to the task since it can predict future trajectories, deals with multiple inputs and outputs, and includes explicit constraints. Elmaz and Yücel applied data-driven models in conjunction with MPC to regulate the outputs from biomass gasification by adjusting the equivalence ratio, thus showing the advantages of using an anticipatory rather than a purely reactive control method [3]. Stanger et al. designed a hierarchical structure for dual-fluidized-bed gasification in which a high-level MPC was responsible for controlling both the amount of product gas and the gasification temperature, while a lower-level MPC looked after bed-material circulation; this approach was tested both in simulation and through experimental work on a 100 kW pilot plant [4]. The key industrial insight is architectural in nature: complex gasification control can be broken down into interacting predictive layers rather than being forced into a single, unified optimization problem.

Neural networks are useful for reducing the computing demand of prediction whenever first-principles models are too slow. Wang and Ricardez-Sandoval incorporated recurrent neural networks into the dynamic process optimisation of a pilot-scale entrained-flow gasifier and examined load-following and co-firing situations [2]. Faridi et al. used a long short-term memory model as part of an MPC formulation and tested temperature regulation against a physics-based fluidised-bed model, finding that they achieved a low steady-state error and fast computation [5]. Given that such surrogate-assisted MPC indicates promise for large facilities in Saudi Arabia, it is because the optimisation has to be carried out within a practical control interval. Yet the validity of the surrogate must be restricted to the operating envelope; carrying out extrapolation beyond the conditions on which it was trained constitutes a process risk, not simply a statistical error.

A good controller should be able to tell the difference between set-point optimisation and constraint protection. While the optimizer can aim to increase hydrogen yield, cold-gas efficiency or syngas throughput, the hard constraints must include the maximum temperature, pressure, oxygen slip, minimum steam ratio, refractory limits, the capacity of the downstream sulfur-removal unit, the compressor surge margin and the requirements for turbine fuel. Soft constraints allow for temporary compromises in return for a penalty. This approach is more reasonable than using an AI controller with no constraints since it explicitly retains the knowledge of the process. It also enables operators to review the situation: engineers can see which constraint is in effect and can understand why the suggested action differs from current practice.

Explainable machine learning may improve the quality of supervisory decisions. Bongomin discovered that ensemble models are becoming more commonly used for predicting gasification and pointed to SHAP, sensitivity analysis and partial-dependence methods as means of identifying important variables [9]. The 2025 study on the entrained-flow Transformer also employed SHAP to show that the oxygen-to-coal ratio is a major predictor [11]. In the case of an operating plant, interpretability must be given in the form of engineering context rather than as a decorative dashboard. Any suggestion to increase the oxygen supply should be accompanied by the predicted impacts on temperature, the H2/CO ratio, carbon conversion, syngas heating value and the active constraints. Furthermore, explanations can help in spotting false correlations resulting from maintenance conditions, analyzer bias or past operator practices.

The most advanced level is plant-wide economic optimisation. In an integrated facility a gasifier does not have a single optimal operating point which is independent of the rest of the system; the best operating conditions for the reactor vary according to hydrogen demand, the steam balance, the power price or dispatch requirement, the efficiency of oxygen production, the capacity of the downstream cleanup unit, the availability of carbon capture and the state of the equipment. Economic MPC can convert these external conditions toward dynamic targets for the lower-level controllers; the objective function can include the cost of the feed, oxygen and steam consumption, net power output, the value of hydrogen, emissions intensity, penalties for degradation and the risk of violating constraints. Since each of these terms has a different level of uncertainty, the optimiser should apply conservative margins until the model's performance has been proven over a number of seasons and operating modes.

Table 2. Comparison of control and optimization families for Saudi integrated gasification facilities.

Control family	Core mechanism	Main strength	Main limitation	Best Saudi deployment role	Evidence
PID / cascade / ratio control	Reactive feedback around local set points	Transparent, fast, proven and easy to validate	Weak coordination of nonlinear interactions and future constraints	Safety-compatible regulatory foundation	[18,21]
Kalman-filter state estimation	Model plus sensor residuals reconstruct hidden states	Uses sparse sensing and exposes internal dynamics	Sensitive to model structure and noise assumptions	Soft sensing, sensor validation and state awareness	[1,24]
Model predictive control	Optimizes predicted multivariable trajectories under constraints	Handles coupling, delay and explicit operating limits	Requires a validated dynamic model and reliable computation	Supervisory regulation of temperature, flow and syngas targets	[3,4]
Neural-network MPC / dynamic	Data-driven dynamic model embedded in	Captures nonlinear behavior with lower online	Extrapolation and training-domain risk	Bounded-envelope predictive control after rigorous validation	[2,5]

Control family	Core mechanism	Main strength	Main limitation	Best Saudi deployment role	Evidence
surrogates	online optimization	model cost			
Explainable machine learning	Ensemble / deep prediction with feature attribution	Fast soft sensors and interpretable variable influence	Data bias, overfitting and regime transfer	Advisory prediction, anomaly context and optimizer support	[9-12,14-16]
Federated digital twin	Synchronized physical, mechanistic and data-driven models	Scenario testing, soft sensing, health and optimization in one architecture	Integration, governance and bidirectional-security complexity	Cross-unit coordination of gasifier, ASU, cleanup, H_2, steam and power	[6,7]
Plantwide economic optimization	Slow supervisory objective balancing value, efficiency and constraints	Converts integrated-facility interactions into operational targets	Depends on trustworthy models, costs and constraint definitions	Final maturity layer for utility, carbon and economic optimization	[6,28,29]

6. Digital Twins and Analytics-Based Operational Intelligence

Digital twins offer a way of organizing this hierarchy. An effective industrial twin goes beyond simply providing a three-dimensional visualization or acting as an offline simulator; it must include synchronized plant data, state assessment, model execution, prediction, health assessment and a controlled procedure for making recommendations or updating set-points. Jankovic et al. developed a digital twin for a biomass-to-gas plant that combined online process simulation, soft sensing and optimization, and as a result achieved gains in efficiency linked to control and operating-point optimization [6]. In their 2025 review, Akhator and Oboirien claim that many power-plant twins are still incomplete since there is no bidirectional data communication and suggest a gasification twin that incorporates science-informed dynamic models, data-driven models, actual data and pre-executed simulations [7].

For a Saudi integrated facility the twin should be federated not centralised into a single fragile setup. The gasifier twin should exchange boundary conditions with models of the air-separation unit, the syngas-cleanup process, the hydrogen system, the steam network, the combined-cycle unit and the carbon-management system. Each of the submodels can operate at the right level of fidelity and update rate. Estimators which are fast might run once every second; predictive control every several seconds or minutes; equipment-health models every few minutes; and economic optimisation at even slower intervals. This kind of architecture permits graceful degradation since the plant will be able to carry on using validated regulatory control if the high-level model or data service becomes unavailable.

It is important to have a system of governance for models. Each soft sensor and surrogate must have an owner, a version number, a defined boundary for the training data, a validation dataset, a performance threshold and a rollback procedure. When delayed laboratory or analyzer readings become available, drift monitoring should compare the predicted values with the actual measurements. Retraining must be controlled rather than carried out automatically in the case of models which are relevant to safety. Synthetic data can be of use when there are few experiments: Qi et al. used generative adversarial networks and random-forest screening to extend their hydrothermal-gasification datasets [13]. However, synthetic observations should be used to advance model development and not be taken as evidence of how the plant is behaving. Acceptance in an industrial setting will only occur if real operating data is available for the various situations including startups, steady states, turndown, feed changes and disturbance scenarios.

7. Saudi Deployment Framework for Integrated Energy Facilities

The situation in Jazan renders it especially clear how integration can be implemented. According to Aramco's 2021 report, there was a joint venture involving the IGCC power plant, the air separation unit and various other associated assets, with the feedstock provided by Aramco and the venture itself producing power, steam, hydrogen and other utilities [28]. It therefore follows that the gasifier's performance should be assessed in terms of its system-wide effects; boosting raw syngas output would not be advantageous if the air-separation unit becomes the bottleneck, if the cleanup system reaches its sulfur-loading limits, or if the steam system is driven into an inefficient let-down. On the other hand, a slightly reduced reactor efficiency might be justified during a transient should it help to maintain the hydrogen specifications or the stability of the combined cycle.

A deployment framework from Saudi Arabia should therefore focus on five different areas of outcome. The first of these is safety and availability, encompassing trip avoidance, refractory protection, stable pressure and controlled behaviour of the slag or solids. The second is syngas quality, which entails maintaining a stable content of hydrogen and carbon monoxide, controlling contaminants, having an appropriate heating value and guaranteeing the H2/CO ratio is suitable for use in downstream processes. The third is resource efficiency, meaning the use of oxygen, steam, feedstock, electricity and auxiliary fuel per unit of useful output. The fourth is environmental performance, covering carbon intensity, flaring, sulfur handling and compatibility with carbon capture. The fifth is flexibility, that is, the capacity to alter the load or the emphasis on the product without incurring excessive transition losses. Although Vision 2030 gives the general reason for industrial digitalisation and for improved efficiency, it is the plant-level metrics that make the strategy operational [29].

The severe climate in Saudi Arabia introduces certain requirements when it comes to equipment. Any electronics used outdoors, as well as analyzers, cooling systems and communication gear, have to be able to withstand high ambient temperatures together with dust and salinity found in coastal areas. The sample conditioning has to stay stable even after long periods of operation and in the face of fouling. When choosing redundant measurements of temperature and pressure, failure independence should be considered rather than just having simple duplicates. Diagnostics are necessary for critical transmitters to detect problems such as impulse-line plugging, thermocouple drift and valve stiction. Wireless sensing could be useful for noncritical rotating or structural components, but safety and closed-loop control signals must still comply with existing reliability and cybersecurity standards. The benefit of smart instrumentation resides in its ability to deal with diagnosable uncertainty, not in increasing the number of connected devices.

A good first step when it comes to putting the system into use is to introduce it as a “trusted advisory” layer. The historical plant data are cleaned and brought up to date; the state estimator and the soft sensors are validated off-line; and the system then provides predictions, together with constraint margins and suggested set points, without making any changes to the control system. Only after operators have shown that the advisory layer remains stable under a range of representative conditions can some of the recommendations be incorporated into supervisory closed-loop operation, with rate limits and an automatic fallback mechanism in place. This step-by-step approach is more defensible than directly implementing end-to-end autonomous control since it develops evidence, increases operator familiarity, and establishes governance at the same rate as the technical capabilities advance.

The second objective is to carry out predictive control with respect to the known bottlenecks. For instance, the gasifier temperature, the syngas flow and the H2/CO ratio can all be controlled together while taking into account oxygen availability, the steam balance and the cleanup constraints. The third objective is to achieve economic coordination between the various units. A digital twin should be able to estimate the marginal effects of changes in the gasifier on the production of power, hydrogen and steam, after which a slow optimizer can produce feasible targets. Industrial data must be stored together with pertinent context such as the operating mode, the feed batch, the maintenance state, the analyzer status and the current control configuration. Otherwise, machine-learning models might end up learning correlations that are caused by plant procedures rather than by physical principles.

8. Reliability, Cybersecurity, Human Factors and Performance Governance

The risk characteristics of the plant are altered by smart control. Typical failures are generally noticeable in the form of transmitter faults, actuator faults or problems with controller tuning; digital failures can involve silent data corruption, model drift, time-synchronisation errors, cyber intrusion, stale predictions or an optimisation service which continues to provide maths-wise possible but operationally unsuitable targets. The control architecture must therefore incorporate the principle of layered defence. The safety instrumented systems stay independent. The basic regulatory control is still able to operate steadily. The advanced controllers receive data that has been verified via controlled interfaces. High-level optimisation cannot circumvent hard interlocks, permissives or equipment protection.

Cybersecurity has to align itself with the information flows that are generated by analytics and digital twins. In order to achieve bidirectional supervisory control, it is necessary to have segmentation, to provide authenticated services, to implement least-privilege access, to keep a record of all changes and to have a manual fallback procedure. The online control system should preserve a validated mode that is resident on the edge and which continues to function even when communication is lost, at the same time blocking any unauthorized commands.

Performance evaluation must make use of a hierarchy of metrics. The hierarchy includes metrics that are based on a closed loop, such as integral error, settling time, constraint violation and disturbance rejection. Those relating to the process comprise carbon conversion, cold-gas efficiency, H_2/CO stability, tar or contaminant burden and specific oxygen or steam use. Asset-related metrics are refractory exposure, valve travel, compressor margin and unplanned downtime. Economic metrics involve useful energy output, hydrogen value and variable cost. Environmental metrics cover direct emissions, flaring and captured carbon. A controller is only to be regarded as successful if improvements at one level do not result in hidden deterioration at another.

The evidence in the reviews also indicates that uncertainty should receive greater consideration. A number of machine-learning studies claim to achieve excellent accuracy on their test sets, including ensemble or neural models which have very high coefficients of goodness of fit [8,9,12]. While this is encouraging, industrial control needs prediction intervals, the ability to detect out-of-distribution cases, and sensitivity to measurement bias. A model which is accurate on the average could still be unsafe close to a refractory limit. Hybrid formulations that combine conservation laws with machine-learning-based residual correction are therefore promising since they can maintain the basic physical coherence while learning the systematic discrepancy between the plant and the model. The 2025 modelling review does similarly regard hybrid and AI-integrated approaches as a major area for the future [17].

9. Research Gaps and Future Roadmap

There are still several research gaps before highly autonomous gasification becomes a regular practice. Firstly, most of the studies involving advanced control are based on pilot scale, rely on simulation, or focus only on particular biomass systems. Secondly, instrumentation research should shift from demonstrating the sensitivity of analyzers to assessing maintainability, calibration frequency, the availability of the sample system, and lifecycle costs. Thirdly, predictive controllers need to be benchmarked against clear regulatory criteria; improvements must be reported in terms of process and economic performance rather than merely in control-error statistics.

Fourth, subsequent research should combine gasifier control with the constraints that come downstream. The processes involved in syngas cleaning, sulphur recovery, hydrogen separation, steam production, gas turbine operation and carbon capture all have dynamic limitations which cannot be taken into account by using only an objective function for the reactor. Fifth, digital-twin research has to show that safe bidirectional deployment is possible. Although present frameworks specify the components that are needed, full industrial coordination, model governance and cybersecure actuation are still less developed [7]. Sixth, data-driven approaches require improved transfer learning between different feedstocks and scales. Reviews of machine learning as it applies to gasification continually point out that dataset heterogeneity, interpretability plus generalisation remain unaddressed challenges [9,10,15,16].

The following five-stage approach is suggested. In the first stage, instrument integrity is established by means of rationalised sensors, continuous supervision of analyser health, synchronising the historian, carrying out reconciled mass and energy balances, and using a governed tag dictionary. In the second stage, process state estimation and soft sensing are introduced for variables which are either delayed or not measured. In the third stage, constrained model predictive control is put into use within a defined operating envelope, starting off in an advisory capacity and then progressing to being used under supervisory control. In stage four, a federated digital twin is incorporated, the aim being to integrate equipment health, process prediction and scenario testing. In stage five, plant-wide economic and carbon optimisation is carried out for the gasification, oxygen, cleanup, hydrogen, steam and power systems. Progress from one stage to the next must be based on documented performance gates and not on a calendar deadline.

Research should also look into resilient optimization in the case of extreme or uncertain conditions. Saudi facilities could experience changes in demand, equipment having to operate at a reduced rating, dust events, limitations regarding cooling, and changes in product priorities. Robust MPC, stochastic optimisation, and scenario-driven digital twins are capable of turning uncertainty into explicit margins. Explainable models should be assessed not just on the basis of the accuracy of their predictions, as well as with regard to whether their feature attributions stay stable throughout various operating regimes. Research into sensor selection should make use of estimator observability and value-of-information metrics in order to determine where the addition of a further thermocouple, a composition analyzer or a differential-pressure measurement results in the greatest decrease in control uncertainty.

Finally, the future architecture should support learning without uncontrolled adaptation. Plant data can continuously reveal model mismatch, but automatic retraining of a controller after every drift event would make validation impossible. A safer pattern is monitored learning: the production model remains fixed; a candidate model is retrained in a segregated environment; both run in parallel; performance is compared over predefined scenarios; and only an approved version is promoted. This approach brings software lifecycle discipline into process control and allows Saudi operators to capture the benefits of AI while retaining auditable engineering responsibility.

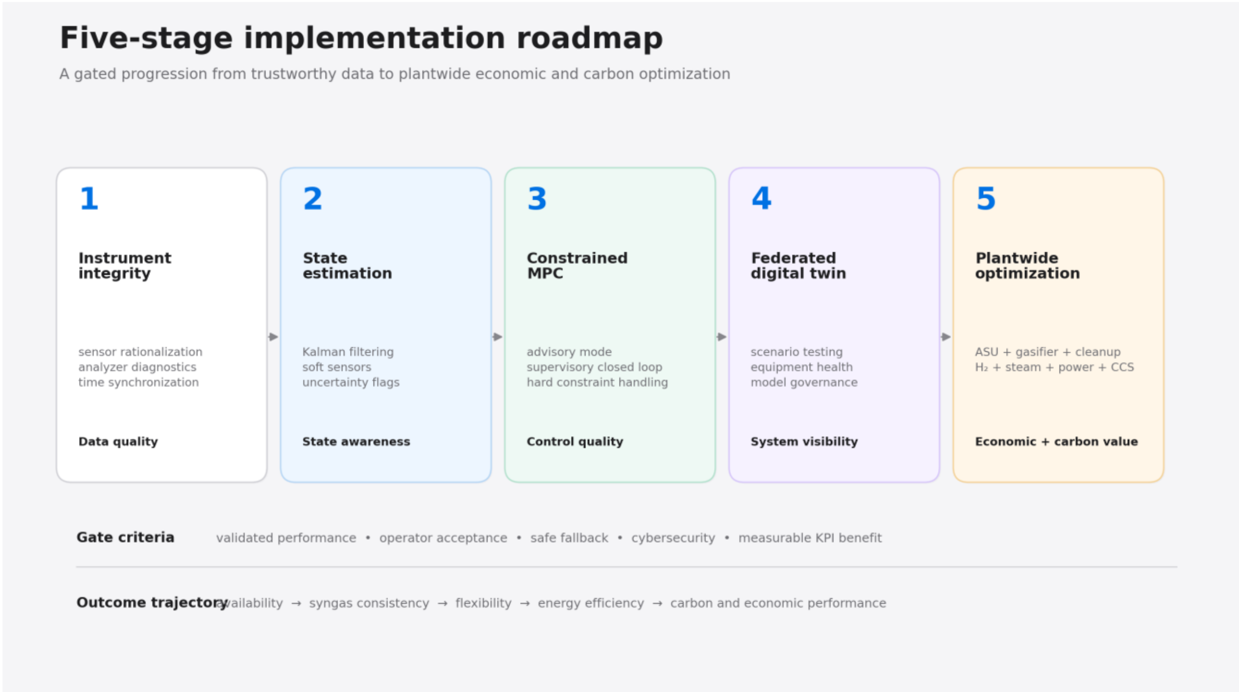

Figure 2. Five-stage Saudi implementation roadmap from instrument integrity to plantwide economic and carbon optimization.

10. Conclusions

The smart control linked with gasification is more appropriately viewed as an integrated system for measurement and decision-making rather than as a single advanced algorithm. Advances in the area, as shown in the literature from 2020 to 2025, have been gradual and cover online spectroscopy, state identification, dynamic neural models, model predictive control, explainable machine learning and digital twins. If the number of sensors is low then Kalman filtering can be used to reconstruct the internal states of the gasifier [1]; data-driven and neural models are capable of modelling the nonlinear dynamics [2,3,5]; constrained MPC can coordinate the various interacting variables and has already been proven in experimental pilot studies [4]; and digital twins can connect sensing, simulation, soft sensing and optimisation [6,7].

The best course of action for Saudi Arabia is to adopt a multi-layered system which is intended to achieve a variety of integrated utility objectives. As an example, Jazan demonstrates the need to co-ordinate gasification with the supply of oxygen as well as with the production of power, steam and hydrogen [28], and Vision 2030 provides a national framework for improving industrial productivity, for developing digital capabilities and for transforming the way in which energy is used [29]. The proposed course of action consists of keeping independent safety systems in place and making sure that there is strong regulatory control, before bringing in validated system estimation, supervisory model predictive control, equipment-health analytics and finally plantwide economic optimisation. This step-by-step method lowers the risk of implementation and makes sure that each digital layer can be held responsible for particular operational benefits.

The research should therefore concentrate on improving the quality and range of the decisions that operators and conventional control systems are able to make, rather than on replacing them. Future work in this area should involve data on sensor dependability, uncertainty, constraint behaviour, fallback performance, cybersecurity architecture and plantwide economics as well as on algorithmic accuracy. When these requirements have been met, smart instrumentation and predictive optimisation will be in a position to help gasification plants operate closer to their safe economic limits, stabilise syngas quality, increase the flexibility of hydrogen and utilities, reduce avoidable energy losses and contribute to lower-carbon industrial development in Saudi Arabia.

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