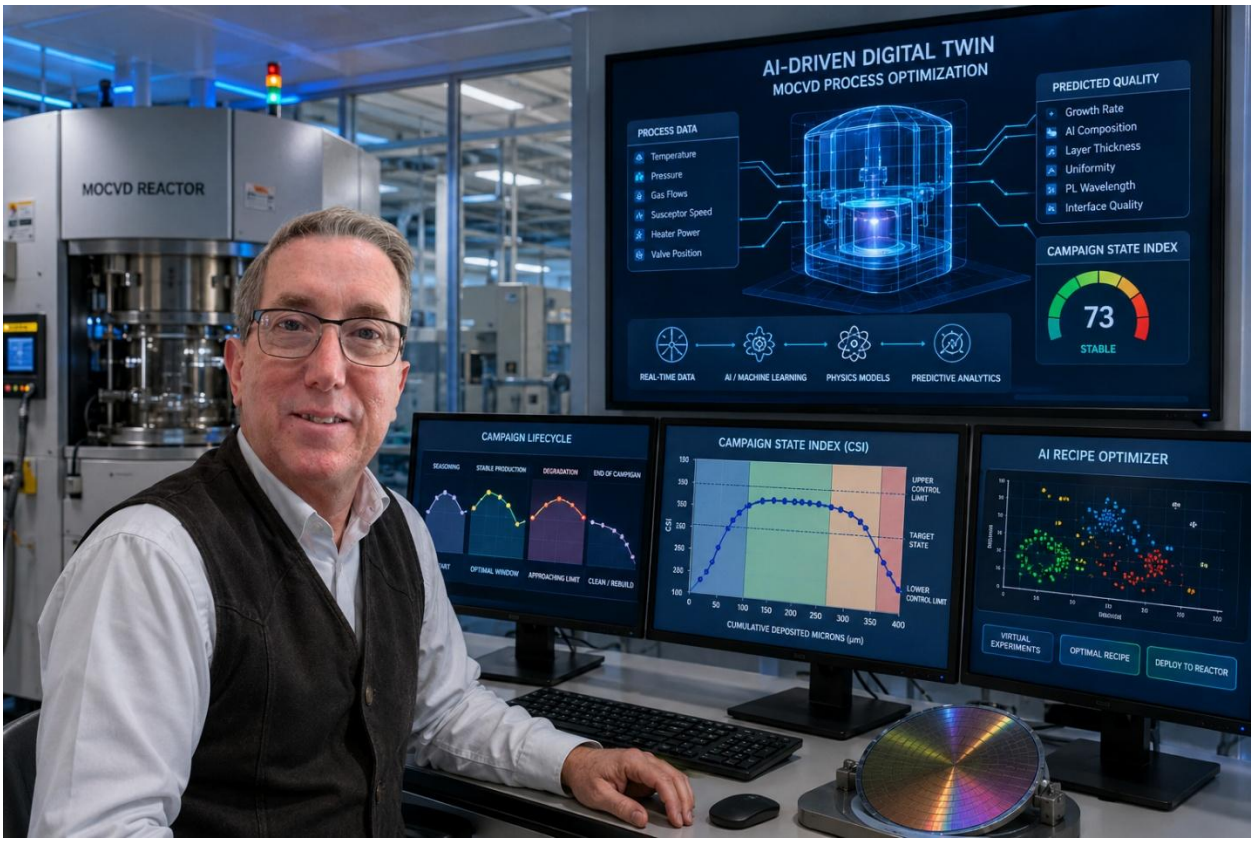
Dynamic Engineering Factors Based on Campaign State Index (CSI) for AI-Driven MOCVD Process Control



Process Control using Engineering Factors

For decades, MOCVD process engineers have relied upon empirical process relationships commonly referred to as **Engineering Factors**. These factors represent the observed sensitivity of an epitaxial process to small adjustments in individual reactor parameters. Rather than relying solely on theoretical models, Engineering Factors were developed through years of production experience, controlled experiments, and continuous process optimization.

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Examples of Engineering Factors include relationships such as:

- +/- XX sccm AsH_3 → +1 nm photoluminescence (PL) wavelength
- +/- XX sccm TMAl → Increased aluminum composition
- +/- XX mbar reactor pressure → Increased growth rate
- +/- XX °C susceptor temperature → Reduced PL wavelength
- Increased wafer rotation speed → Improved within-wafer uniformity

These empirical relationships became invaluable tools for experienced process engineers. When a measured characteristic deviated from target, the engineer would apply one or more Engineering Factors to determine an appropriate recipe adjustment for the next production run. This iterative approach successfully produced high-quality epitaxial structures for many years.

However, Engineering Factors possess several important limitations. Most are derived under a specific set of reactor conditions and are often assumed to be independent of one another. In reality, MOCVD growth is governed by complex nonlinear interactions between temperature, pressure, precursor flow rates, reactor geometry, campaign history, surface chemistry, and cumulative deposition. As a reactor progresses through a production campaign, these sensitivities may change significantly. An Engineering Factor that accurately predicts a 1 nm wavelength shift early in a campaign may produce a different response after hundreds of microns of cumulative deposition have altered the reactor environment.

Artificial Intelligence extends the concept of Engineering Factors by learning these relationships directly from historical manufacturing data. Rather than modeling a single process variable, AI simultaneously evaluates hundreds of process parameters and their interactions across thousands of production runs. The Digital Twin continuously updates these learned relationships as new manufacturing data become available, allowing the predicted Engineering Factors to evolve with the changing condition of the reactor.

Instead of relying on fixed empirical adjustments, the AI system estimates the current reactor state, predicts the expected response to potential recipe modifications, and recommends the combination of process changes most likely to achieve the desired epitaxial result. For example, rather than suggesting a fixed increase in arsine flow to

correct photoluminescence wavelength, the Digital Twin may determine that a smaller adjustment in arsine flow combined with a slight reduction in reactor pressure and a minor increase in susceptor temperature will produce a more accurate correction while preserving growth rate and composition.

In a fully autonomous implementation, the Digital Twin becomes an intelligent process advisor capable of evaluating multiple recipe modifications before the next production run begins. During growth, the system continuously compares live reactor data against its predicted model. When deviations are detected, the AI estimates their impact on epitaxial quality and can either recommend corrective actions to the process engineer or automatically adjust selected process parameters within predefined engineering limits.

This represents the evolution of MOCVD process control—from static Engineering Factors developed through human experience to adaptive Engineering Factors continuously learned, refined, and optimized by Artificial Intelligence.

Dynamic Engineering Factors

$$\boxed{\text{Engineering Factor}_i = f(\text{CSI},\ \text{Recipe},\ \text{Reactor History})}$$

The Digital Twin uses the current Campaign State Index (CSI) to calculate a new set of Dynamic Engineering Factors for each production run. These factors represent the predicted sensitivity of the reactor to changes in individual process variables at its current operating state. As the CSI evolves throughout the campaign, the Engineering Factors evolve with it.

The CSI therefore becomes the independent variable that determines the predicted process sensitivity of the reactor at any point during the production campaign.

The Dynamic Engineering Factors become the adaptive process gains used by the AI Recipe Optimizer to calculate the optimum recipe corrections for the next production run.

$$\Delta Recipe = f(\text{Target} - \text{Measured}, \text{Dynamic Engineering Factors})$$

Traditional MOCVD process control has long relied upon empirical process relationships known as Engineering Factors. These relationships describe how small adjustments to

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reactor operating parameters influence critical epitaxial characteristics such as photoluminescence wavelength, alloy composition, growth rate, layer thickness, and wafer uniformity. Examples include empirical observations such as increasing arsine (AsH_3) flow by approximately 3 sccm to produce a 1 nm increase in photoluminescence wavelength or reducing reactor pressure by several millibar to increase growth rate.

These Engineering Factors have proven invaluable for production process control and have traditionally been developed through years of engineering experience, designed experiments, and statistical process optimization. However, they are generally treated as fixed process sensitivities, implying that a given recipe adjustment will always produce the same result.

Production experience demonstrates that this assumption is not always valid.

As an MOCVD reactor progresses through a production campaign, cumulative epitaxial deposition gradually alters the reactor's thermal characteristics, gas flow dynamics, surface chemistry, and precursor utilization efficiency. Consequently, the reactor's response to a particular recipe adjustment changes continuously throughout the campaign.

The Campaign State Index (CSI) provides a quantitative representation of this evolving reactor condition. Rather than assuming Engineering Factors remain constant, the Digital Twin continuously estimates the current CSI and predicts how each Engineering Factor changes as the reactor evolves.

For example, early in a campaign when the reactor has recently completed seasoning, increasing arsine flow by 3 sccm may increase photoluminescence wavelength by approximately 1 nm. As cumulative deposition increases and the reactor approaches the end of the campaign, that same 3 sccm adjustment may produce only a 0.6 nm wavelength shift or require a simultaneous adjustment in reactor pressure or growth temperature to achieve the desired result. The Engineering Factor itself has become dynamic because the reactor state has changed.

Artificial Intelligence continuously learns these Dynamic Engineering Factors by correlating historical process data, real-time reactor measurements, post-growth metrology, and the current Campaign State Index. Instead of applying fixed empirical corrections, the Digital Twin predicts the process sensitivity appropriate for the reactor's current operating condition.

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The AI can then evaluate thousands of possible recipe combinations before the next production run, selecting the combination of process adjustments most likely to achieve the desired epitaxial characteristics. Within predefined engineering limits established by the process engineering team, the Digital Twin can recommend recipe modifications or automatically implement predefined recipe adjustments within validated engineering limits.

Dynamic Engineering Factors represent the evolution of traditional process engineering into adaptive manufacturing intelligence. Rather than replacing engineering knowledge, Artificial Intelligence captures decades of empirical process understanding and continuously refines it as every production campaign contributes new information to the Digital Twin. The result is a manufacturing system that not only understands how a reactor performs today but also predicts how its behavior will evolve throughout the remainder of the campaign.

The Campaign State Index does not directly control the reactor. Instead, it continuously modifies the Engineering Factors that determine how the Digital Twin predicts the reactor will respond to future recipe adjustments.

Conclusion

For decades, Engineering Factors have served as the foundation of practical MOCVD process control, allowing experienced process engineers to compensate for normal process variation through empirical recipe adjustments. While highly effective, these factors have traditionally been treated as fixed relationships that do not fully account for the evolving condition of the reactor throughout a production campaign.

This paper introduces the concept of **Dynamic Engineering Factors**, in which the sensitivity of the reactor to individual process variables is continuously recalculated as a function of the **Campaign State Index (CSI)**. By combining historical manufacturing data, real-time reactor measurements, post-growth metrology, and Digital Twin technology, Artificial Intelligence can continuously predict how the reactor will respond to future recipe modifications under its current operating condition.

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Rather than replacing engineering expertise, this approach extends decades of accumulated manufacturing knowledge by transforming static empirical Engineering Factors into adaptive process models that continuously learn from every production campaign. The Campaign State Index provides a quantitative measure of reactor condition, while the Dynamic Engineering Factors translate that condition into predicted process sensitivities that can be used for recipe optimization.

The result is a practical framework for adaptive MOCVD process control that supports predictive process optimization, reduced engineering development time, improved wafer-to-wafer repeatability, increased manufacturing yield, and the potential for autonomous recipe optimization within validated engineering limits. Although demonstrated here for 800 nm GaAs edge-emitting lasers, the methodology is broadly applicable to other III-V semiconductor technologies and represents a logical next step toward intelligent, self-learning semiconductor manufacturing.

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