Real-time Learning Temperature Control for Increased Throughput in LED Manufacturing

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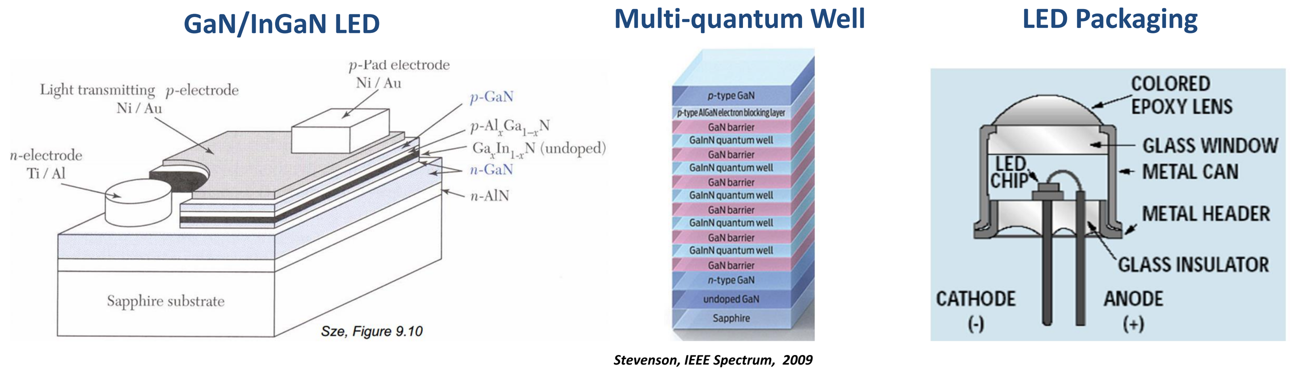
SC SOLUTIONS

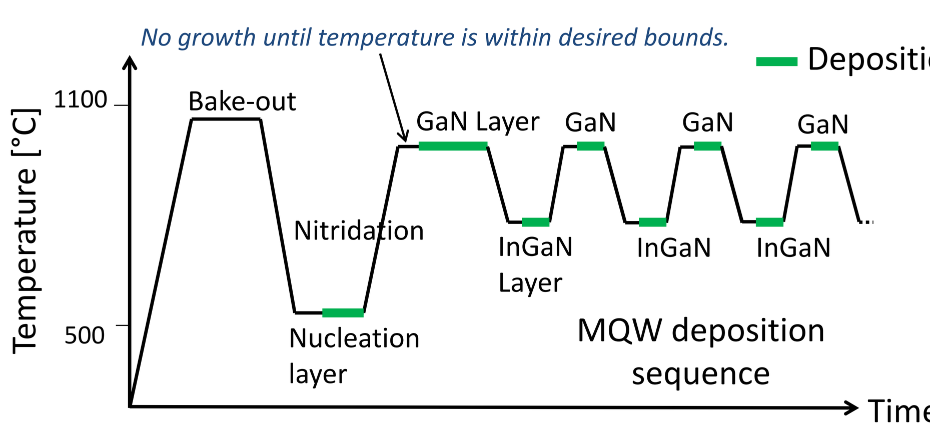
Project Goals

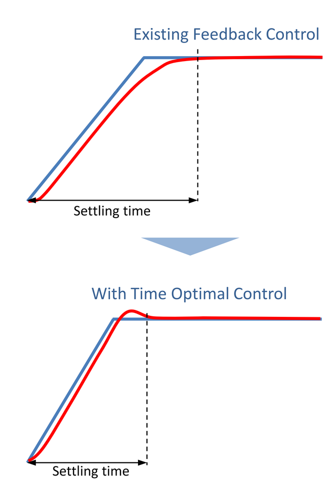
1. **Develop a new generation of temperature controllers that can achieve significant reductions in settling time while maintaining temperature accuracy and uniformity.**
2. **Demonstrate sufficient improvement in throughput to commercialize the controllers and reduce the cost of LEDs.**
3. **Demonstrate the feasibility of model-based optimal/learning control that can maximize performance.**

Background – MOCVD for LED

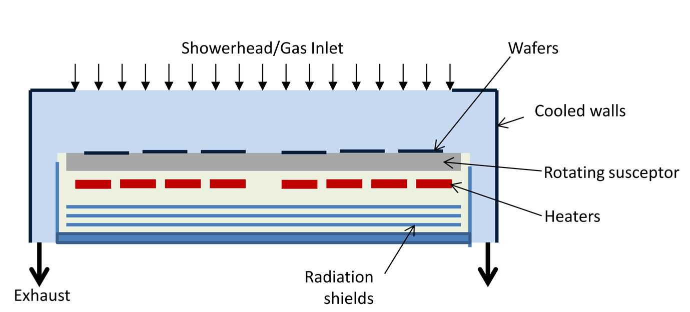


- ❑ **In production of the LED, there are many sequential growth steps at different temperatures.**
- ❑ **The temperature during growth significantly effects the color (and other properties) of the emission.**
- ❑ ***Reducing the transition time from one growth step to another can significantly improve throughput.***



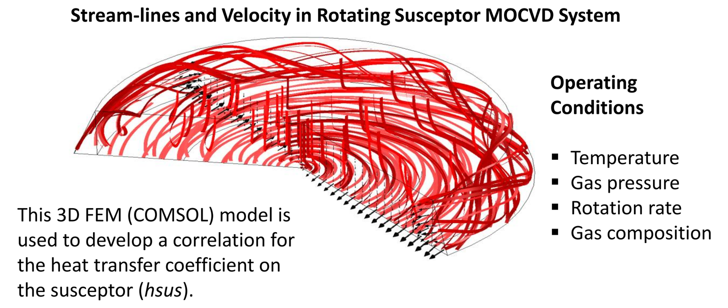


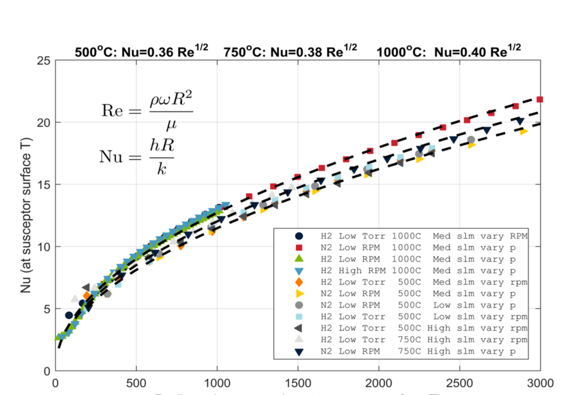
Physics-based Model of MOCVD

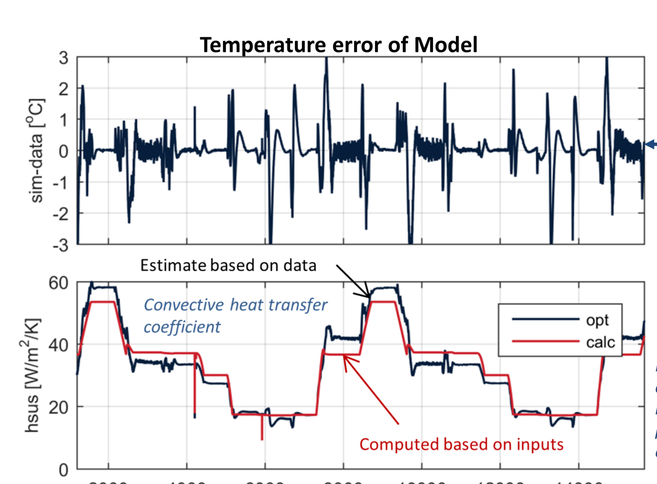


Thermal Model of MOCVD System

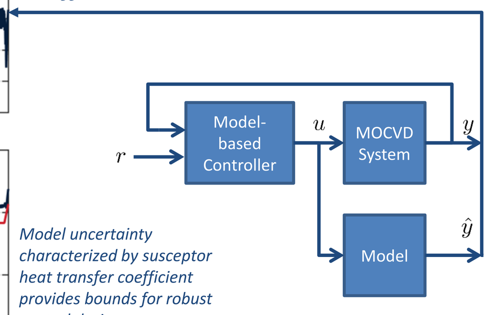
- **An accurate heat transfer model was developed for Model-based Control (MBC) Design.**
- **Dominated by radiative heat transfer.**
- **Conduction is important within solid components.**
- **Convection matters since operating conditions (temperature, gas composition, pressure, rotation rate, etc.) vary considerably during growth, and these parameters affect convection.**





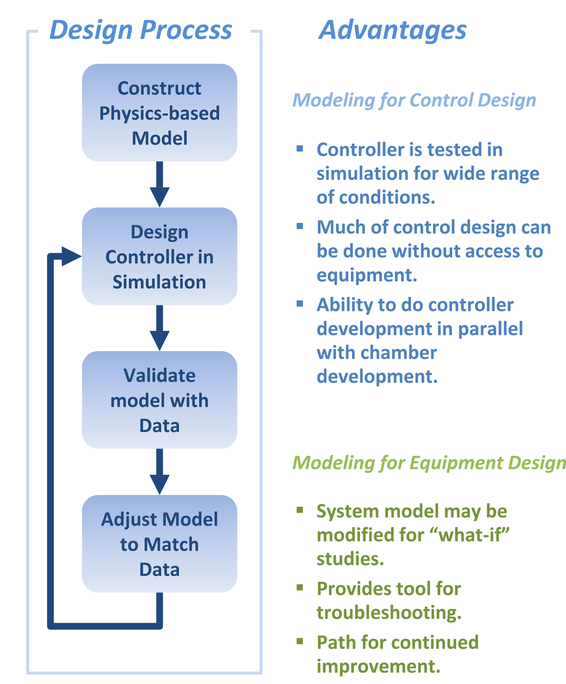


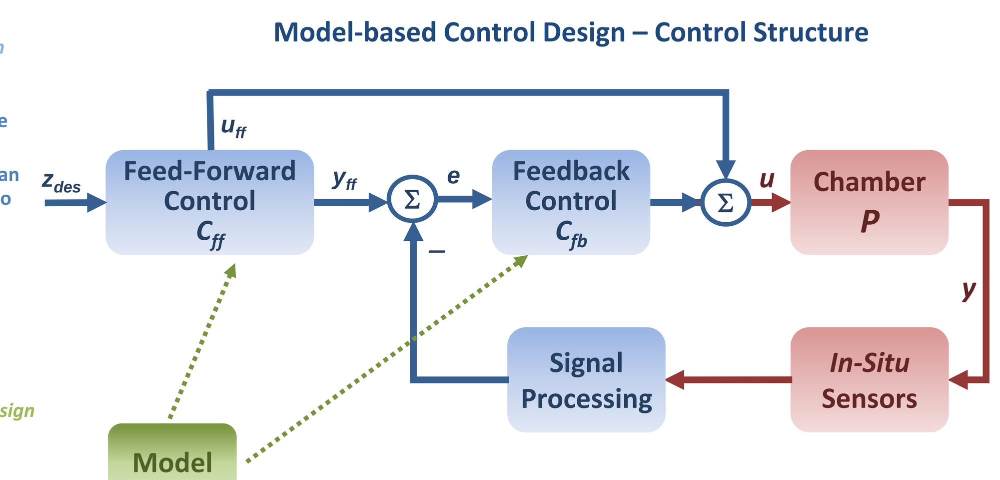
Difference between model and data

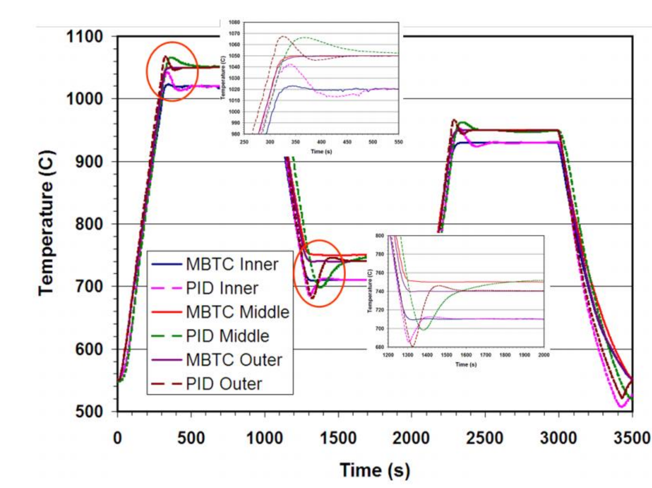


- **Model was validated for a wide range of temperatures, pressures, rotation rates, gas flows, and gas compositions.**
- **Model errors are small (<3°C) over the entire range of operating conditions.**
- **Model uncertainty (characterized by susceptor convection, hsus) was small, but must be addressed in control design.**

Model-Based Control (MBC) Design



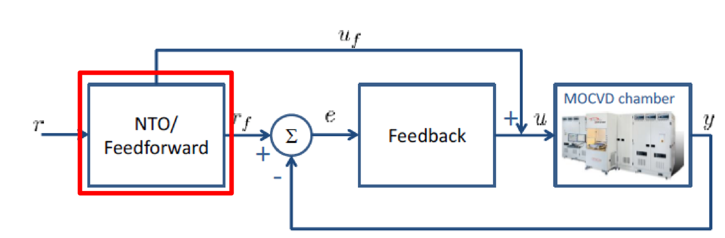




- **Model-based control has been demonstrated to provide significant improvements by reduction of settling time, as shown by this data.**
- **The addition of Feedforward control (FF) could dramatically improve this reduction.**
- **Under this program, algorithms for using the model to develop FF strategies have been developed.**
- **Several strategies have been investigated, including a robust FF strategy that can accommodate model uncertainty.**

Optimal Feed-Forward Control

- ❑ **Improvement of ramp up performance is desirable to increase the throughput.**
  - Faster ramp up can reduce recipe time
- ❑ **Time Optimal Control**
  - Feed-forward control that uses the plant model and desired output to generate an optimal output trajectory and corresponding control inputs
  - Computation of FF profiles is completed prior to the actual use
- ❑ **The time optimal problem has been approximately solved by using NTO algorithm.**
- ❑ **Improved time optimal algorithm has been discovered during Phase I research.**



Near Time Optimal Approach

- Approximately solves the time optimal problem. The solution is not the theoretical global time-optimal, but a practical near-optimal solution.
- r must be chosen carefully. The time-optimal performance of the NTO depends on a fair estimate of the maximum ramp rate.

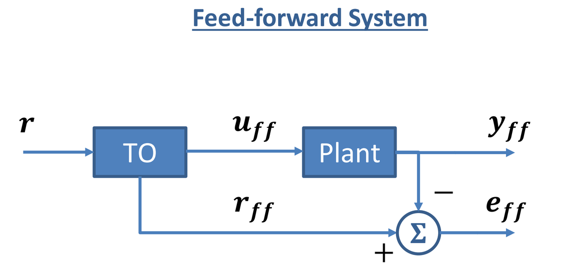
True Time Optimal Approach

- Optimizes time directly automating the generation of r.
- The heuristic logic associated with the NTO implementation can be removed.

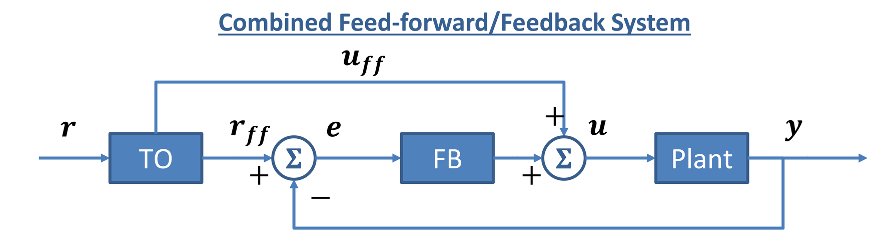
Robust Feedback Control

- ❑ **Model parameters are not known exactly, and feedforward controls are sensitive to the uncertainties.**
- ❑ **The feed-forward controls are combined with a feedback control for robustness.**
- ❑ **Feedback controller corrects for errors caused by model parameter uncertainties.**

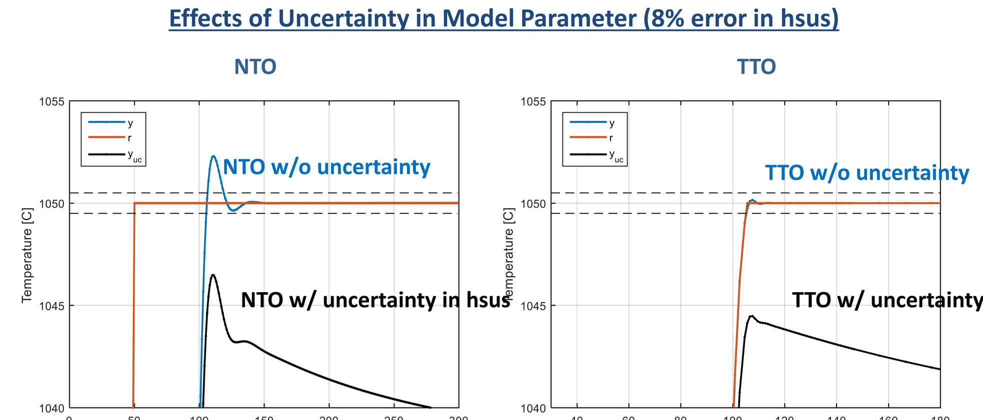
Feed-forward System



Combined Feed-forward/Feedback System

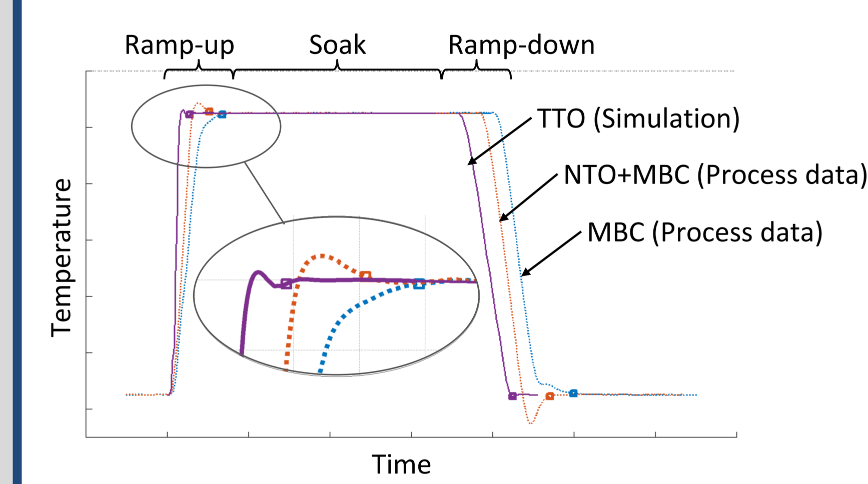


Effects of Uncertainty in Model Parameter (8% error in hsus)



Experimental Validation

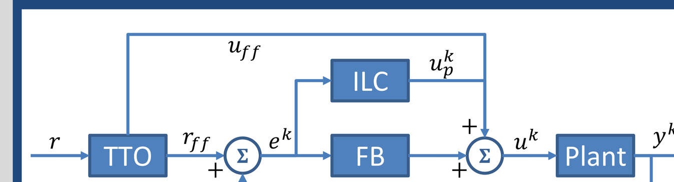
- ❑ **Near time-optimal (NTO) and MBC have been tested on MOCVD Equipment and compared to simulation.**
- ❑ **The TTO method has been simulated, but we expect to begin hardware testing soon.**

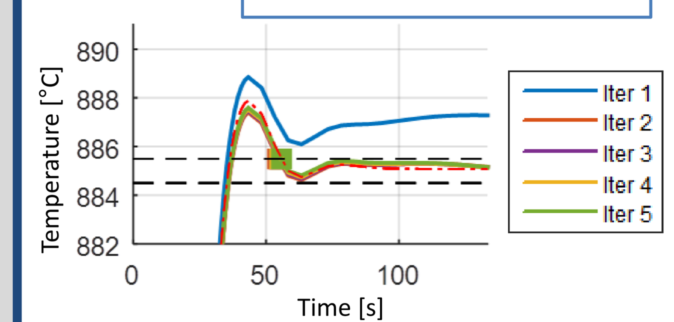


Method	MQW cycle time	Ramp-up time
MBC (Exp)	1	1
NTO+MBC (Exp)	0.916	0.778
TTO (Sim)	0.843	0.367

- ❑ **Both NTO and TTO showed significant reduction in MQW cycle time.**
- ❑ **Most of the reduction was achieved in the ramp-up. Reduction in ramp-down time is limited by cooling rate of susceptor.**

Iterative Learning Control (ILC)





- ❑ **ILC was implemented to improve system robustness .**
- ❑ **ILC uses both models and measured data to improve the control performance from trial to trial (run-to-run), i.e., it learns the system dynamics through repetitive trials.**
- ❑ **The system dynamics thus learned can be effectively used to reduce the error in subsequent trials.**
- ❑ **Simulation with ILC shows improvement in tracking response with each iteration.**

Summary of Accomplishments

- ❑ **Physics-based models have been built that match experimental data.**
- ❑ **An estimator has been built to provide quantitative estimates of the model parameters.**
- ❑ **NTO feedforward control was developed and tested on commercial MOCVD reactor.**
- ❑ **An improved true time-optimal algorithm, TTO, was discovered and tested in simulation.**
- ❑ **Feedback control and ILC were integrated into control architecture for greater robustness.**
- ❑ **Demonstrated effectiveness of integrated control approach in simulation and experiment.**

Proposed Phase II Program Effort

- ❑ **Use learning algorithms to estimate best nominal plant model and uncertainty envelope for use in the Robust NTO & FB controller.**
- ❑ **Integrate the identified uncertainty envelope into a Robust NTO design.**
- ❑ **Automate existing NTO & FB design to use updated nominal and uncertainty model on-the-fly.**
- ❑ **Build the software prototype of the integrated Robust NTO & FB controller and demonstrate on commercial MOCVD equipment.**

Acknowledgments

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About SC Solutions

Our mission: To become the premier supplier of model-based control and optimization technology for the LED and semiconductor equipment industries

Our Areas of Expertise:

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- physics-based modeling
- software development
- optimization
- system identification
- fault diagnostics
- signal processing

Our Industries:

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