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DMDII FINAL PROJECT REPORT

Integrated Scheduling and Control for Real-Time Optimization of Factory Operations

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14. ABSTRACT

THE PROJECT WILL ADDRESS GAPS DIRECTLY BY INTEGRATING PRODUCTION SCHEDULING WITH LOWER LEVEL PROCESS CONTROL AND AUTOMATION DECISIONS.

15. SUBJECT TERMS

OPTIMIZATION, KENT DISPLAYS

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TABLE OF CONTENTS

I. EXECUTIVE SUMMARY

The real time optimization of continuous processes which operate at steady-state conditions is a well-established technology supported by sophisticated, but practically oriented, commercial software running online models. The same cannot be said of batch processes and roll-to-roll processes which move through many operating regimes, can involve complicated step logic, and generally require significant human intervention. There is no analogous commercial offering in this space and the research reported in the literature is limited to simulation studies where automation logic and human intervention is not thoroughly considered.

Furthermore, because batch processes (as well as, short term campaigning on roll-to-roll processes and discrete part manufacturing) are generally used to produce a suite of products, their economic performance is highly dependent on the quality of production planning and scheduling that directs their overall operation, and the fidelity by which these plans are carried out in the manufacturing process. Commercially available planning and scheduling software, while capable of developing schedules using sophisticated algorithms, rely on human intervention for execution of production schedules, as well as monitoring the process to respond to circumstances that would require reworking schedules to keep them feasible. The lack of the integration of production scheduling with the process control system represents a significant manufacturing capability gap in achieving real-time optimization of batch processes.

The project described here addresses these gaps directly by integrating production scheduling with lower level process control and automation decisions. In our solution, scheduling decisions are passed to the control system for executions while schedules are directly influenced and updated by feedback from the real time operation of the control system, providing increased responsiveness of the production process.

This project also addressed specific production planning problems encountered in small scale, roll-to-roll manufacturing as found at Kent Displays. While an integrated solution could be applied at Kent Displays, their roll-to-roll manufacturing line can benefit greatly from application of our methods as standalone solutions. Their high priority technology gaps involve the need to predict product failure rate based on raw material inspection data. Then use the predicted yields to optimize the assignment of raw material lots to finished products so that raw material consumption is minimized. Furthermore, there is a need to schedule finished product campaigns so that product transition costs are minimized.

Our integrated solution embodies a scheduling optimization module that communicates with a lower level process control system and is informed by a companion delay monitoring and prediction module. This module interprets the state of the process control logic, including manual interventions required for process execution, to test the feasibility of the current schedule, the results of which are used to re-optimize the schedule if necessary. In addition, our scheduling model expands the scope of the optimization problem to include operator interventions and batch recipe manipulation to achieve a more comprehensive optimization in batch operations.

We operationalized these methods in an integrated computing environment where closed loop scheduling and control actions can be impressed on a simulated manufacturing process. We used this test environment to debug and demonstrate the utility of our solution. We designed our test environment it such a way that the process simulator can be replaced by communication with a real process control system. With an appropriate optimization model communicating directly with a control

system, our solution will achieve integrated scheduling and control for real-time optimization not available with commercial platforms. Since scheduling is considered part of Manufacturing Execution Systems we call our solution Manufacturing Execution Optimization (MEO). Assuming certain commercial software licenses are obtained, the MEO environment will be available to DMDII members for their use.

Using a simulation of a single batch reactor, we demonstrated quantifiable improvement to manufacturing costs resulting from a schedule produced using our MEO solution as compared to the scheduling approach now in use in The Dow Chemical Company.

The solutions we developed for production planning the roll-to-roll process at Kent Displays were validated by their use on the firm's production line. These solutions are:

- A multi-variate statistical model to predict product failure rate
- A mixed-integer linear programming model to plan raw material consumption
- A mixed-integer linear programming model to schedule finished product campaigns

Based on all the results we obtained from our testing regime of the MEO system and the application of the solutions for Kent Displays we report the following conclusions and recommendations:

- The MEO solution
    - Improves schedule performance in real time by appropriately responding to delay events in the system
    - Has the following limitations:
        - Application is best suited for batch processes and discrete part manufacturing
        - The methods as developed are limited to moderate size problems
    - Will be implemented within Dow's environment
    - Delay monitoring and prediction module can be applied with a manually derived production schedule to provide improved visibility to process operators
    - There would be value in implementing the system at a DMDII testbed for additional experimentation and validation of its general purpose nature
    - Should be explored for implementation in Simatic IT
    - Explore data driven methods to predict scheduling delays
- Tailored solutions for Kent Displays
    - KDI have benefited and will continue to use the solutions
    - KDI should explore advanced image classification of their raw material rolls
    - Extend the capability of the campaign planner
- Workforce Development:
    - Find internal workforce development champion(s)
    - Pick one position and one national certification
    - Engage local and regional ecosystem partners
    - Build a pipeline model that addresses local needs
    - Fit partners into pipeline
    - Expect the need to test and adapt the approach

II. PROJECT REVIEW

Our project was based on two primary objectives. One was directed at large scale manufacturers: build, test and document a functioning integrated software system with the following attributes:

- Produces an optimal short term production scheduling that accounts for shared resources, material transfers, inventory management, processing capacity limits, changeover for product transition, operator interventions, and sequencing logic in the control system
- Predicts future process delays using a detailed model of a plant's discrete automation logic
- Re-optimizes the schedule before a predicted delay actually occurs
- Operates in real time performing closed-loop optimization of a simulate batch process or a real one under the control of a digital control system
- Is based on methods that can be tailored to the requirements of a broad class of manufacturing processes and their simulation platforms or control systems

The other primary objective was to satisfy the production planning and scheduling needs of a small manufacture using a roll-to-roll process. We built and deployed at Kent Displays the following tools:

- A multi-variate statistical model to predict product failure rate
- A mixed-integer linear programming model to plan raw material consumption
- A mixed-integer linear programming model to schedule finished product campaigns

Our technical approach to create the MEO work flow environment draws on established methods in the fields of **Optimal Production Scheduling** using mathematical programming, **Discrete Event Systems** for formal design and analysis of automation logic, and **Real Time Optimization** currently applied to continuous processes in the petro-chemical industry. These methods provide a general abstraction of a production environment allowing our solution to apply to a wide variety of manufacturing processes. For the purposes of demonstration and to focus our development efforts, we linked the MEO solution to a simulation of a target process operated in **Siemens Simit** simulation platform. These complimentary methods will be briefly discussed.

Optimal Production Scheduling

We chose the Resource Task Network (RTN) formulation as the modeling paradigm for creating a scheduling optimization model. In a RTN representation, a process is composed of two types of entities, resources and tasks. Resources include process units, materials, utilities, etc. Tasks are all types of process operations that transform or seize and release resources. Describing a scheduling problem with the RTN formulation results in a mixed integer linear program that is easily solved by modern optimization engines. A number of successful applications of RTN-based scheduling tools have been reported, with model extensions such as multi-extent resource balances, resource limit balances, and resource slacks. Furthermore, a state-space formulation of RTN models was developed for reactive scheduling of mixed batch/continuous plants, with lifted state variables to record task history.

The RTN formulation is an effective foundation for developing a general purpose, real time module for scheduling optimization. However, it treats many process variables as fixed parameters (e.g., batch processing times) and does not account for decisions dependent on the automation logic (e.g., material transfer between two batch steps). Accordingly, to represent automation logic into our models, we extended the RTN formulation in the following ways.

- Generalized modeling of tasks to account for multi-step tasks
- Developed parameter updates to incorporate process information
- Added field operators as a resource to allow scheduling of human interventions
- Developed methodology to account for delay information (obtained by analyzing automation logic) from delay prediction module

The utility of our enhanced RTN formulation was demonstrated on with the simulation of our test process. However, the general nature of the formulation is readily applicable to a wide range of manufacturing processes. It only requires an appropriate definition of tasks and resources that make up the manufacturing operation.

Discrete Event Systems

While the RTN formulation is an effective approach for computing an optimal production schedule, practical considerations limit it to an abstraction from the true dynamics of the process so that an optimal solution can be computed quickly enough for online operation. An important dynamic component, omitted from the scheduling model, is the plant's automation system, which makes the low-level discrete decisions that drive the plant's behavior. A key issue that we addressed with our MEO solution is the mismatch between the model of the plant used to optimize the scheduling and the actual behavior of the plant, enforced by the automation system.

For example, even for a batch reaction which is modeled as a sequence of subtasks to represent individual steps, each with a fixed duration, the transitions between those steps as enforced by automation system may be dependent upon the state of other pieces of equipment in the plant (which, in turn, have their own sequences of steps). Thus, a schedule computed using a local representation of the steps may not actually be feasible when executed in the plant, even in the absence of disturbances.

To monitor the execution of a schedule, we developed a Delay Monitoring and Prediction module (DMP) based on a finite transition system that models the plant's automation logic augmented with historic data on the amount of time the system spends in each step. With this detailed model of the plant's dynamics, we treat the current schedule as a specification of the desired system behavior, and apply formal model checking to determine whether that specification is violated. This online monitoring consists of comparing the current state of the plant (in real time) to a set of forbidden states that were produced during model checking. If the plant is found to be in a forbidden state, then the resulting delay can be extracted from the DMP and sent back to the scheduling problem. When it is, we extract relevant information to explain the infeasibility, and reschedule.

This model is used online to detect when an existing schedule is no longer feasible, due to runtime disturbances. Determining the states, corresponding to a given schedule, which are no longer feasible amounts to solving a set of supervisor synthesis problems.

In the state-space RTN model, the status of the process is indicated by the state variables, and information obtained by analyzing the automation logic is represented by additional constraints involving those state variables.

The information is sent to the optimizer in the form of additional constraints to be included when computing the new schedule

Real Time Optimization

Traditionally, real time optimization (RTO) has been applied to continuous processes to improve the economic performance, solving continuous optimization problems constrained by steady-state process models. More recently, RTO has been extended to allow direct incorporation of dynamic process models, finding its applications to batch processes. We have developed an advanced framework by incorporating RTN-based optimization model, which enables closed-loop optimization of operating decisions both in the production scheduling and the process control levels. MEO does not require the steady-state assumption to run as it directly handles process dynamics in optimization. It takes additional steps to process data and update model constraints before and after optimization, in communication with production scheduling and process automation systems. A precursor to the MEO system has been proven to work with the pilot applications at Dow.

The development of the MEO platform focused on providing a framework to accommodate and integrate enhanced optimization and delay monitoring, which were observed lacking in the precursor application in Dow. The MEO software platform (Figure 5) contains:

- Delay monitoring: Combination of the supervisory control model derived from the automation logic and a model checker.
- Optimization model: The RTN-based optimization model in an algebraic modeling language such as GAMS.
- Simulated control system: A simulation model to mimic process dynamics and automation logic in SIMIT. The simulated model defines inputs and outputs consistent with the real plant and is used to verify the optimized solutions obtained from the optimization model informed by the DMP.
- Executive program: A Python-based script performing the central control functions of the MEO system. The script will perform
    - MEO execution control: coordinate information flows and trigger MEO runs
    - Data pre-processing: update parameters and constraints of the optimization model based on process measurements and delay monitor outputs.
    - Model solution post-processing: polish optimization solution and convert optimization result to process input.
    - Interface routines: enable real-time data communication between modules.

Siemens Simit Simulation

Siemens SIMIT simulation platform enables comprehensive tests of automation applications and provides a realistic training environment for process operators. SIMIT graphic user interface makes it possible to create simulations (without real hardware) in order to test automation software. Simit offers various automatic modeling functions for simple, rapid simulation modeling. Simulation models and components can be automatically generated, for instance with the aid of template-based imported data. Testing and optimization can be carried out either using a real or a virtual automation system.

The SIMIT model for a batch process plant that include various unit operations such as reactor, intermediate storage, filter, check tanks, virtual operator and truck offloading was developed as part of this project and is a documented deliverable. This model can be used to simulate a typical full scale batch process. Thus, it can be used as a virtual plant for various research activities in this area. However, the closed loop integration of control and scheduling was studied with a reduced model as shown in Figure 1. The reduced model consists of reactor, truck delivery and a virtual operator component and represents a typical batch operation for many chemical companies. The reactor can produce three different types of products using any of the three different types of reactant. The virtual operator logic is implemented to mimic operator who can perform multiple tasks; one task at a time. These tasks involve reactor start, offload truck, sample the reactor, clean filter, and sample check tanks. Since closed loop study deals with only reactor and truck offloading operations, operator has to perform tasks to these to operation in nominal scenarios. While clean filter task is used to introduce an artificial delay in sampling the reactor to study abnormal scenarios where operator might not be available to perform certain task at the particular time. The reduced model and its automation (low level control) logic that is used for the closed loop study and the full SIMIT model without any automation are fully documented in companion reports to this one.

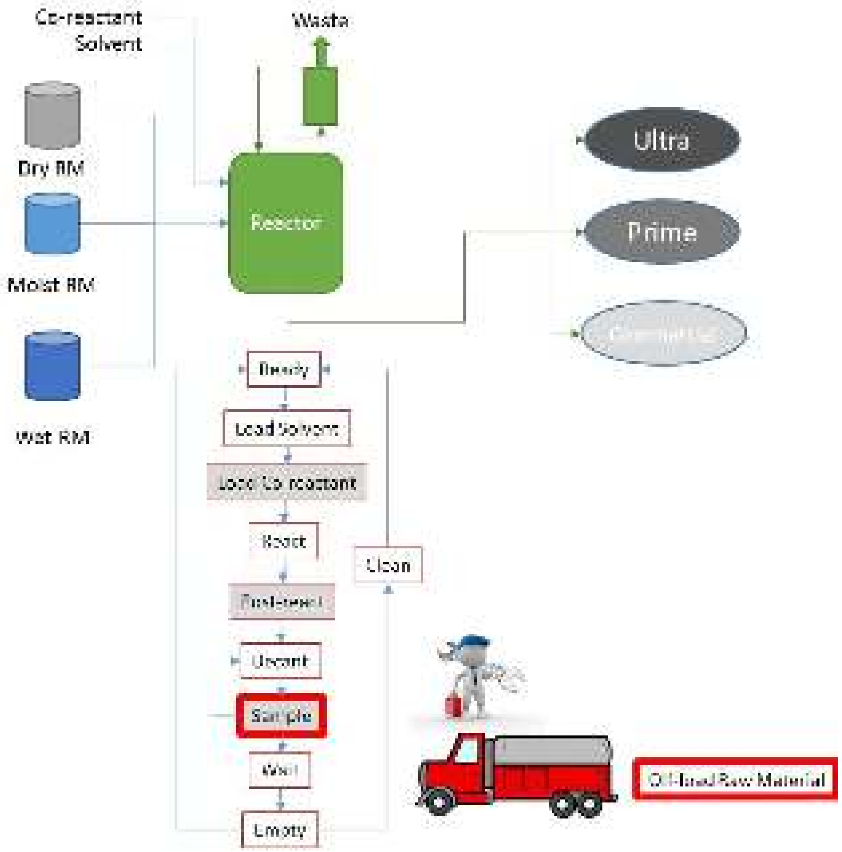

Figure 1 Test process for closed loop testing of the MEO system

As seen in Figure 1, this batch process plant produces multiple types (or grades) of products using multiple grades of raw material. Batch processing time, production cost and quantity of product produced per batch vary with the quality of raw material used. Thus, production plan for a typical batch plant involves decision of which raw material to use for particular batch and how to sequence these batches to meet the demand with minimum lateness and with least cost. The former is known as planning problem while later is known as scheduling. Thus, production planning in the batch process plant involves simultaneous planning and scheduling. For most of the cases this requires to solve an MILP problem to achieve all objectives optimally. This problem often becomes computationally intractable for large planning horizon. On the other hand, uncertainties, such as order cancellation, machine failure, uncertain execution times, etc. are hallmark of any real world application, which makes rescheduling inevitable. This requires planning and scheduling in parallel with plan execution to accommodate any unforeseen disruptions and react accordingly. In other words, it demands active planning and scheduling at each time step or whenever a deviation between planned and executed schedule is detected. These are the challenges for which we designed the MEO system. Specific scenarios that demonstrate the performance of MEO will be described next with the accompanying metrics used to measure results.

III. KPI’S & METRICS

In this section, we compare the performances of the MEO solution with Dow’s incumbent solution and an alternative scheduling model provided by Siemens. Performance is evaluated through the use of scenarios that distinguish the strengths and weaknesses of each approach.

The Dow scheduling mode uses a state-space RTN model built such that it can be solved from any input given by Simit without tracking previous decisions or batch end times as is done with the MEO scheduling model. The Dow model also initializes differently than the MEO solution. Furthermore, the Dow formulation of the RTN model is agnostic to past flow rates and their effect on batch end times. A delay is never actually detected. Instead the model will assume the current step will end in the next time step even when the current step’s time in step exceeds the expected value. Consequently, the model is optimistic that the system will return to normal operation in the next time step.

The Siemens scheduling model does not attempt to solve for a proven optimal solution by examining all branches in the solution tree. Instead it borrows the receding horizon and terminal cost concept from Model Predictive Control (MPC) and uses a branch and bound approach with a shorter scheduling horizon (in terms of number of batches) and the introduction of estimated cost for remaining demand from unplanned batches, referred to as future “cost-to-go”. As a result, a relatively small branch and bound problem is solved at each time step to obtain schedule of few batches from which only first batch is executed and problem is resolved with updated feedback from plant for remaining demand in a receding horizon manner. In this approach, the approximate cost-to-go values play an important role and facilitate: (i) tree exploration by considering costs beyond the limited horizon, (ii) decision on which states will be explored first within the planning horizon, and (iii) avoiding exploration of decision branches with inferior solutions.

We use the scenarios defined in the table below to compare these solutions. Each of these scenarios, has two cases. Scenarios 1 through 4 are simulated with and without integrating the DMP module, whereas scenario 5 has different prediction horizons. The key performance indicators for these models are solution time, raw material cost and whether the demand is met on time.

Table 1. Description of scenarios tested

Scenario	Description	Case 1	Case2
1	Two batches are needed to meet the demand. No delays throughout the execution.	Without DMP	With DMP
2	Two batches are needed to meet the demand. *Sample* step is delayed as operator is occupied in cleaning the filter. Initially, there is only the wet reactant.	Without DMP	With DMP
3	Two batches are needed to meet the demand. *Decant2* step occurs as *Decant1* fails. Initially, there is only the wet reactant.	Without DMP	With DMP

4	Six batches are needed to meet the demand. No delays throughout the execution. Prediction horizon is 500 minutes.	Without DMP	With DMP
5	Twelve batches are needed to meet the demand. No delays throughout the execution. Demand exists beyond the initial prediction horizon.	Prediction horizon(450 minutes)	Prediction horizon(600 minutes)

Table 2. Result for tested scenarios

Scenario	Attributes	Dow model	MEO model	Siemens model*
1.1	Solution time(s)	27	25	43
	Raw material cost	5	5	5
	Meeting demand	Yes	Yes	Yes
	Comments			
1.2	Solution time(s)		24	
	Raw material cost		5	
	Meeting demand		Yes	
	Comments		No difference in the cost as there is no delay	
2.1	Solution time(s)	24	26	43
	Raw material cost	15	15	5
	Meeting demand	Yes	Yes	No
	Comments		Dry reactant truck is ordered	Cannot order truck
2.2	Solution time(s)		24	50
	Raw material cost		10	5
	Meeting demand		Yes	No
	Comments		Moist reactant truck is ordered as delay is detected at an earlier time	Delay is captured early but optimizer still used wet reactant
3.1	Solution time(s)	31	24	43
	Raw material cost	15	15	5
	Meeting demand	Yes	Yes	Yes
	Comments		Dry reactant truck is ordered	Even after delay due to 2nd decant, demand met with the lowest cost
3.2	Solution time(s)		24	
	Raw material cost		15	
	Meeting demand		Yes	

	Comments		Dry reactant truck is ordered	
4.1	Solution time(s)	31	27	45
	Raw material cost	55	50	45
	Meeting demand	Yes	Yes	Yes
	Comments		Discretization error	Both demand met on time
4.2	Solution time(s)		27	
	Raw material cost		50	
	Meeting demand		Yes	
	Comments		No change with DMP	
5.1	Solution time(s)	28	23	63
	Raw material cost	100	95	80
	Meeting demand	Yes	Yes	Yes
	Comments	Solved with 10% optimality gap	Solved with 5% optimality gap	Accounts for demand at a later time
5.2	Solution time(s)		29	
	Raw material cost		117.5	
	Meeting demand		No	
	Comments		Solved with 10% optimality gap	

*Execution time for Siemens model includes loading of MATLAB time, which takes between 25-35 s

From the results in the above table, it is important to note that the three different optimization models have approximately the same solution times in all tested scenarios.

In scenario 1, two batches of ultra product are needed to meet the demand. Since there are no delays throughout the execution, both cases (with and without DMP) yield the same result. The ultra product is produced using the wet reactant which is the cheapest reactant available. The demand is met on time, even though batch execution times when using the wet reactant are higher. The raw material cost from all three models are the same.

In Scenario 2, initially we only have the wet reactant and the demand is same as in Scenario 1. However, in this scenario, the operator is occupied in cleaning the filter during the Sample step of the reaction. Consequently, the Sample step extends beyond the nominal duration and end of the batch is delayed. This leads to demand not being met on time using the available wet reactant.

In the case without the DMP (refer Figure 2), the delay due to the operator being occupied in cleaning the filter is only determined near the end of the first batch at 75 minutes. The initial demand at 80 minutes cannot be met due to this delay. In order to meet the demand at 155 minutes, the next batch must use the dry reactant. So a truck containing dry reactant is ordered and offloaded at the appropriate time to start the next batch and the deadline is met.

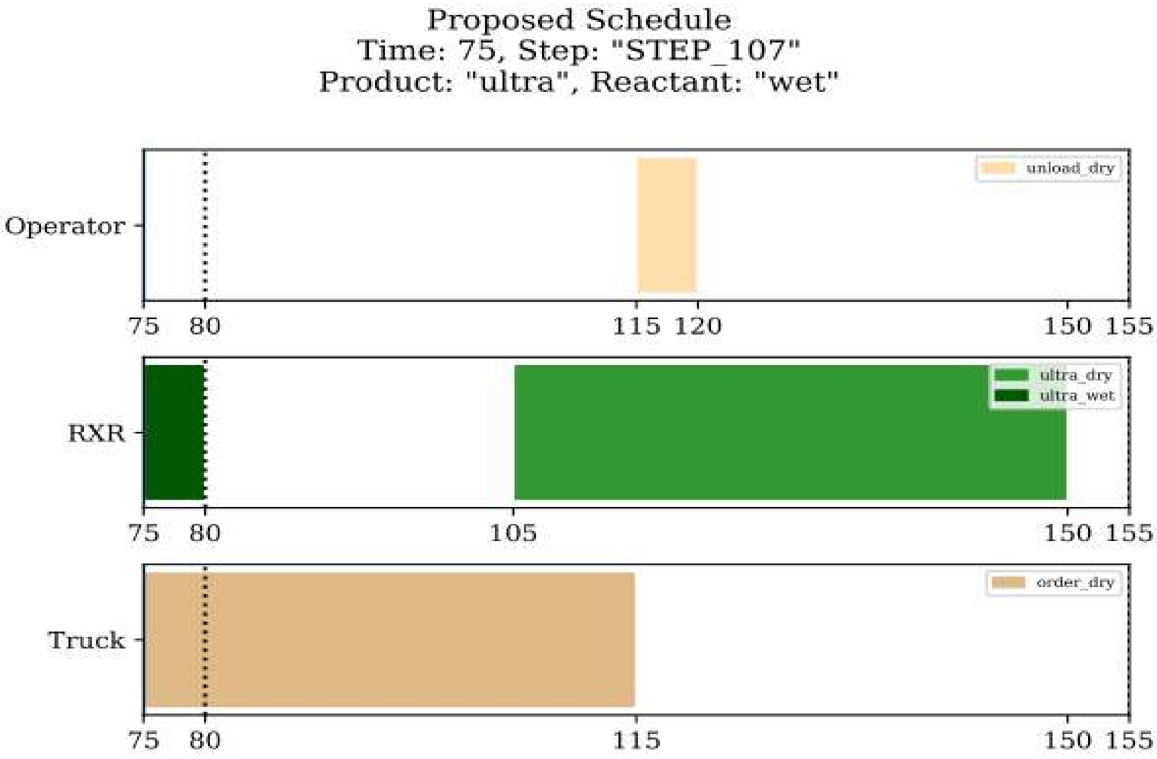

Figure 2. Gantt chart representing the test problem for the case without DMP

On the other hand, for the case with the DMP, this delay is detected at an earlier time of 59 minutes (refer Figure 3). It is communicated to the optimization model, while the first batch is near the start of the Sample step. As a result, the next batch will be able to meet the demand at 155 minutes while using the moist reactant (cheaper than dry reactant). Hence, a truck containing the moist reactant is ordered (refer Figure 4). Thus, by using the DMP module, better decisions are made proactively, resulting in cost savings. The Dow model is not integrated with the DMP so it cannot detect the delay at an earlier time, whereas the Siemens solution cannot meet the demand on time as it does not include the feature of ordering a truck.

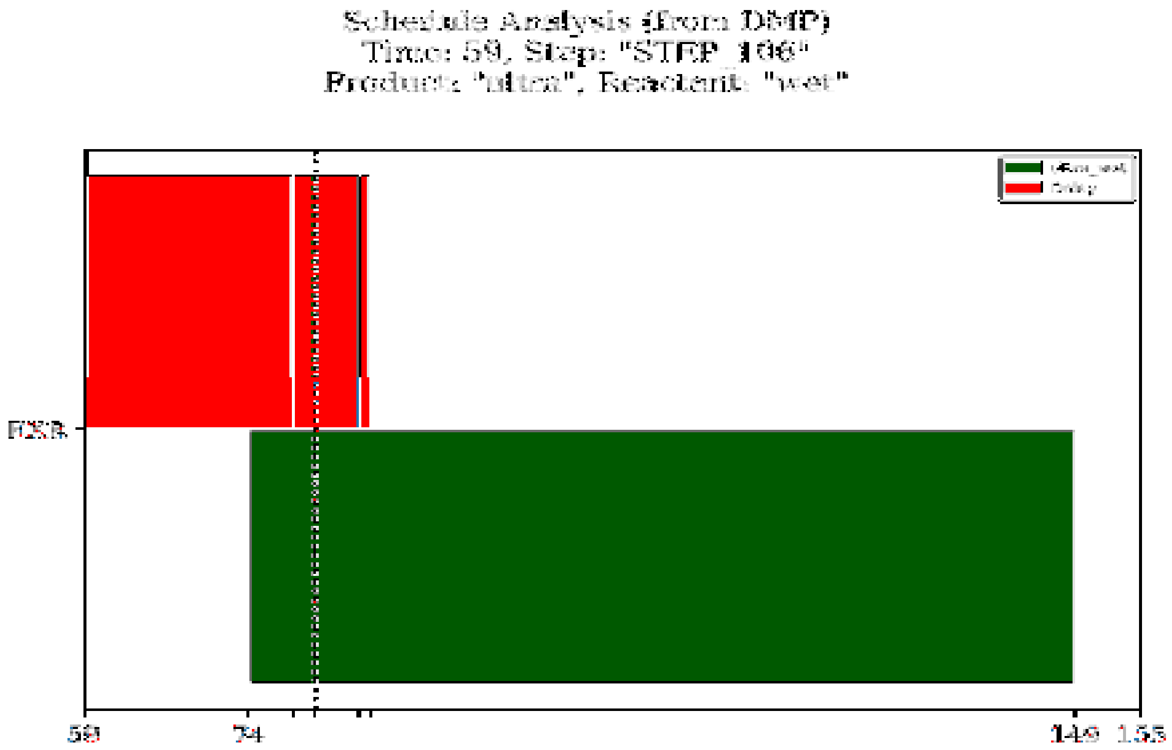

Figure 3. Gantt chart representing early detection of the delay by the DMP

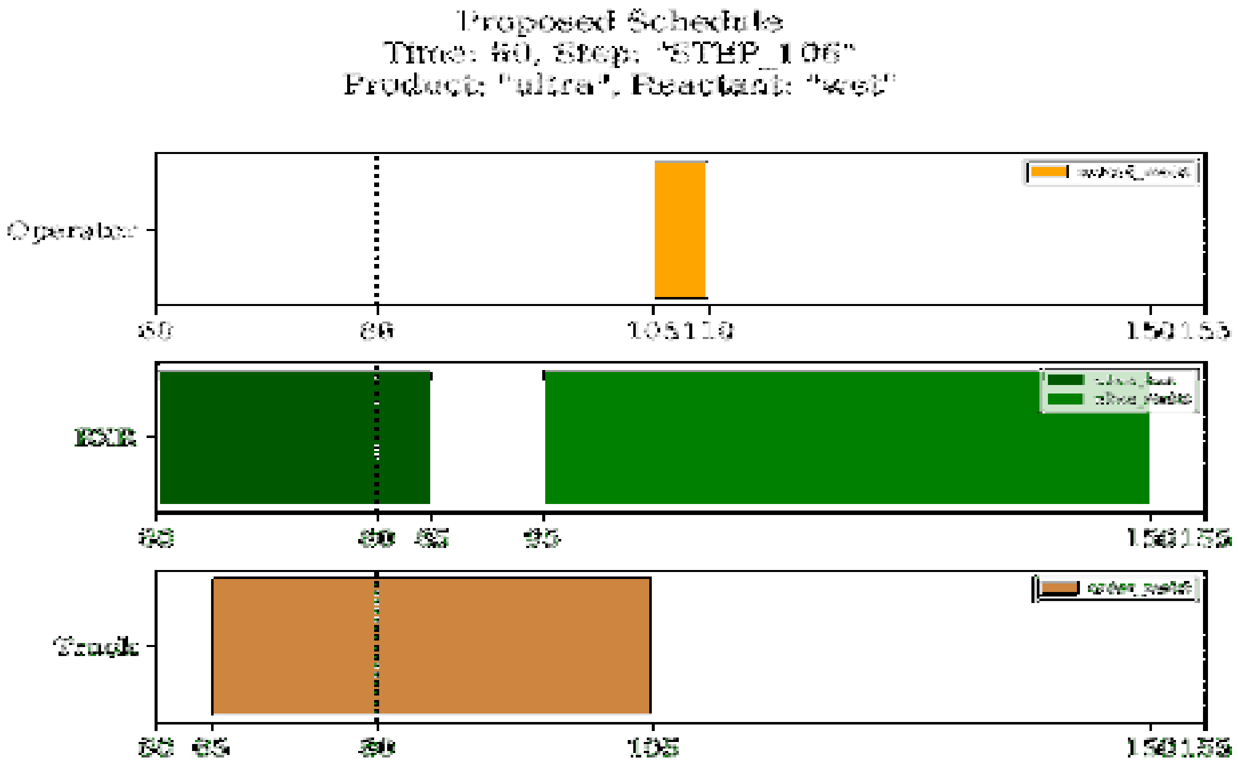

Figure 4. Gantt chart representing the test problem for the case with DMP

In scenario 3, we have the same demand profile as the previous scenarios. This scenario is tested so as to demonstrate the advantage of the optimization model compared to Dow’s incumbent solution. In this scenario, Decant1 step fails and Decant2 step occurs after the Sample step, before the product is released from the reactor. In both cases, we obtain the same result as the optimization model has knowledge about the steps in the process and appropriately accounts for the delay in the end of a batch even without additional information from DMP. In contrast, Dow’s solution does not account for this delay as it has no knowledge about the occurrence of Decant2 step. Despite this shortcoming the demand is still met on time. The Siemens model performs better in this scenario as it uses the exact batch processing times as opposed to the Dow and MEO solutions wherein the batch times are rounded up based on the discretization of the time grid used.

In scenario 4, two batches of each product are needed to meet the demand and there is no delay throughout the execution. The case with the DMP does not make any difference as there are no delays during execution. Similar to the previous scenario, the Siemens model performs better due to its use of exact batch processing times

In scenario 5, a total of 12 batches of different products are needed to meet the demand. This scenario is tested so as to compare the performance of the optimization model with the Siemens solution. Here we compare cases with different prediction horizons. The combinatorial nature of the high demand scenario leads to large number of competitive feasible solutions, hence the branch and bound method takes a longer time to converge to the optimal solution. So, we set the optimality gap at 10% and solve these cases to obtain suboptimal solutions. The Siemens scheduling solution performs better in this case as the demand beyond the prediction horizon is taken into account, while the schedule is being determined. In the future, we could come up with solution methods that could potentially lead to faster computational times.

In conclusion, the MEO solution performs better when the DMP communicates the delay at an earlier time as opposed to Dow and Siemens solution, wherein DMP is not integrated with the optimization model. The Siemens solution is better in some cases as it works on a continuous time grid wherein the exact batch processing times are used as opposed to the Dow and MEO solutions which use a discrete time grid leading to discretization errors.

IV. TECHNOLOGY OUTCOMES

The MEO System, illustrated in Figure 5, integrates the SIMIT simulation, the Scheduling Model, the Delay Monitoring and Prediction (DMP) module, and the Visualization module, with the help of the MEO Executive Program. Key aspects of the integrated systems are:

- The Simit simulation runs in parallel of the other components, communicating through its shared memory with the Executive Program. Its operation is modified by variables passed to it through its shared memory.
- Operation of the Delay Monitoring and Prediction Module and the RTN-based Scheduling Model is controlled by the Executive Program. Their data inputs and resulting outputs are passed via data files to each other and to the Executive Program which can write needed values to Simit’s shared memory.

- The Visualization Module is embedded into the Executive Program

Brief descriptions of each of these components are given in the tables below. Expanded and detailed descriptions are provided in accompanying technical reports for each component.

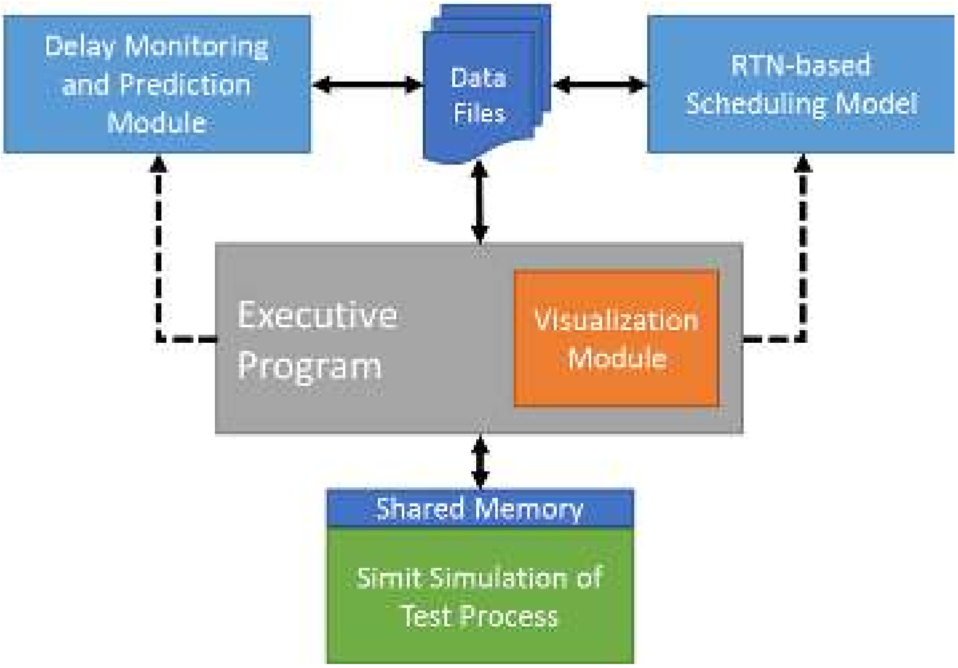

Figure 5. Manufacturing Execution Optimization demonstration system

The basic operation of the MEO System is to start the SIMIT simulation, then repeat the following loop:

1. Read the current state from SIMIT.
2. Run the Scheduling Model to produce a new schedule.
3. Send the new control inputs from the schedule back to SIMIT.
4. Display the schedule using the Visualization module.
5. Run the DMP analysis to check whether the new schedule is feasible, or will be delayed.
6. Display the DMP analysis using the Visualization module.
7. Store the DMP analysis (i.e., the length of the delay, if there is one) by writing an output file, which will be used by the Scheduling Model in the next loop.

The loop is repeated endlessly, until interrupted by the user.

The basic operation of the MEO System can be modified (by setting the MEO Executive Program's runtime parameters, as described in the Executive Program's documentation) in the following ways:

- The DMP analysis can be disabled.
- The Visualization can be disabled.
- A previous run of the MEO System can be "played back" without repeating all of the computations:
  - The SIMIT simulation can be skipped.
  - The Scheduling Model can be skipped.
  - The DMP analysis can be skipped.
  - The Visualization can be turned on or off.

  - For any module that is skipped, the value that it produced in the past execution that is being played back is copied into place as if that module had produced the output.
    - Note that this “opens the loop” between the various components: if SIMIT is being skipped (played back) and the Scheduling Model is being run in every loop, then the new solutions from the Scheduling Model will not be applied to SIMIT, because there is no simulation running.
  - This mode of operation is useful in two main ways:
    - To apply the DMP analysis to an execution that was produced with the DMP module deactivated, in order to check whether it would have detected a delay, had it been active.
    - To quickly visualize the results of a previous execution without having to run the simulation and the associated analyses again.

Scheduling Model	
Brief Description / Purpose	**What is this component?** The scheduling model is part of the optimization module. It determines the start time and sequencing of batches. It communicates with DMP and SIMIT through the executive program. **What is its purpose?** It determines the optimal sequence of batches with the goal of minimizing total cost of production. The start of a batch in SIMIT is triggered by the output from the optimization model. The type of reactant to be used and the product to be produced are determined based on the demand profile. It also communicates shipment information to SIMIT and produces a schedule that is checked by the DMP for its feasiblity **How does it perform its purpose?** The optimization model is written in GAMS, which is a high level modeling system for mathematical optimization. We use the CPLEX solver to solve the Mixed Integer Linear Program. It reads and writes files to be used by the other components
System Requirements	**Hardware requirements** RAM: 8 GB Processor: Intel Core i5-3230 M CPU @2.60 GHz **Operating system requirements** System type: Windows 10, 64 bit OS **Software dependencies (solvers, libraries, etc.)** Use the CPLEX solver to solve the resulting MILP. We have a set of solver options that can be altered as needed. https://www.gams.com/latest/docs/S_CPLEX.html#CPLEX_SUMMARY_OF_OPTIONS **Licenses required** Need to purchase academic or commercial license as appropriate https://www.gams.com/fileadmin/academicp.pdf https://www.gams.com/fileadmin/commercialp.pdf
Input and Communication Medium	**What does it use as input information and data?**

	File that contains all the real time information (state) of the plant (SIMIT). The delay information is communicated by the DMP. It also uses the file containing the demand information **How is this input passed to this module?** The executive program creates these files and calls the optimization model
Output and Communication Medium	**What does it generate as output information and data?** Generates schedule.csv that is used by the DMP to determine if the current schedule is feasible. It also generates an output text file to SIMIT that contains the triggers for starting a batch, shipping the product, ordering a truck etc. **How output is made available?** The executive program uses the generated files and communicates it to SIMIT through shared memory and calls a set of python scripts as part of the DMP module.
Brief Description of Operational Options	**What are the important operational modes/options for the module?** The optimization model reflects the features defined in the test problem. The length of the prediction horizon can be varied and different demand profiles can be fed to the optimization model. Different optimality gaps can also be used to find a feasible solution within a shorter time limit. The main advantages of the optimization model is that it can be paired with the plant at any time, even if the plant has already been running. This is because it uses real time information from the plant to determine the optimal schedule. It can be run as frequently as needed. **How are they selected and controlled?** Most of these options/choices are parameters that can be changed directly in the source code. The demand profile can be altered in the csv file. The time between successive iterations of the optimization model can be altered in the parameters.yaml file.
General Directions to Apply to a New Problem	**What are the steps to tailoring this module to another use case?** To apply this model to a new problem, start by identifying the resources and tasks in the RTN framework. After doing so, identify the resource task interactions and the relative times at which these occur from the start of the task. The initial resource levels need to be defined (or obtained at real time from the plant). The objective function needs to be defined in terms of the decision variables and an appropriate solver has to be chosen to solve the optimization problem. If there are different components in need of information from the scheduling model, appropriate files need to be generated to enable this communication.

Delay Monitoring and Prediction Module (DMP)	
Brief Description / Purpose	**What is this component?** DMP detects delays that will occur because the scheduling model doesn't include the low-level automation logic (including, for example, how the operator interacts with the process) **What is its purpose?** to improve the online scheduling performance

	How does it perform its purpose? supplying additional information about the process dynamics to the scheduler allows it to produce better schedules
System Requirements	**Hardware requirements** standard computer (desktop, laptop, server, etc.) **Operating system requirements** ”any” (Linux/Mac/Windows) **Software dependencies (solvers, libraries, etc.)** Python (2.7+ or 3+) SynthSMV (solver, pre-compiled version included in deliverables) **Licenses required** GPLv3+
Input and Communication Medium	**What does it use as input information and data?** CSV and JSON files (text) **How is this input passed to this module?** the Executive Program produces them from data read from SIMIT and GAMS using helper scripts (Python) provided along with DMP
Output and Communication Medium	**What does it generate as output information and data?** JSON files (text) and PDF files showing the visualization history **How is output made available?** they are written to file during execution
Brief Description of Operational Options	**What are the important operational modes/options for the module?** DMP operates by checking whether the current schedule (from GAMS) is feasible given the current state of the process (from SIMIT) and produces a file that shows how long the delay (if any) will last **How are the selected and controlled?** the Executive Program calls \`st2smv\` as a command-line program after creating its input files and reads the output file that it produces
General Directions to Apply to a New Problem	**What are the steps to tailoring this module to another use case?** • extract the Structured Text code that defines the automation logic • add timing information (how long each step of the process takes) • model any additional constraints (operator can only do one thing at a time, etc.) • create translation scripts to convert from/to the process/simulation (SIMIT in this project) and the scheduler (GAMS/MATLAB in this project)

SIMIT Model	
Brief Description / Purpose	**What is this component?** • This is a plant simulator developed using Siemens SIMIT simulation platform. SIMIT platform comes with inbuilt component libraries for various components of the process industries such as drives, flow network, liquid tanks, gas tanks, etc. • The plant model is connected with virtual controller (soft controller) which enables automation of the simulated plant. **What is its purpose?**

	In the current project, SIMIT model works as a virtual plant which can be used to test proposed MEO system via simulation. **How does it perform its purpose?** It provides plant simulator that mimics behavior of real batch plant. Moreover, automation logic implemented in the virtual controller mimics actual PLC behavior. Thus, the code developed for virtual controller can directly be downloaded on the actual PLC used for automating typical batch plant. Thus, the combination of the plant simulator and the virtual controller enables simulation of a practical situation of a typical batch plant.
System Requirements	**Hardware requirements** PC with the following minimum requirements: 2GHz CPU, 2GB RAM (4GB preferred) , DirectX 9-raphics device with WDDM 1.0- or later driver and a free USB port . SIMIT requires approx. 350 Mbytes of memory on the hard disk **Operating system requirements** SIMIT is a 32-bit application that is released for the following operating systems: o MS Windows 7 SP1 (Professional, Ultimate, Enterprise, 32 and 64 bit versions) o MS Windows 10 Pro and Enterprise (32 and 64 bit versions) o MS Windows Server 2008 R2 (64 Bit) o MS Windows Server 2012 R2 (64 Bit) o MS Windows Server 2016 **Licenses required** o SIMIT 9.1 base license o License for “Flownet” library o License for “Virtual Controller” Note: To change automation logic (for developer), additional licenses of Siemens’ SIMATIC PCS7 and S7 SCL programming language are required
Input and Communication Medium	**What does it use as input information and data?** o SIMIT model takes following input from Scheduler: o Product type, Reactant type, Reactor start command, Demand of each product, command to order a truck of raw material and command for offload a truck (This list and wording should be consistent with Venkat’s list) **How is this input passed to this module?** o SIMIT interacts with GAMS and other modules via shared memory. Internally, plant model interacts with automation (controller) system using virtual controller interface. (Both are inbuilt interfaces in SIMIT)
Output and Communication Medium	**What does it generate as output information and data?** o SIMIT model gives current state of the process (virtual plant), current inventory of products and reactant as well as operator occupancy status as outputs. (This list and wording should be consistent with Venkat’s list) **How is output made available?**

	○ SIMIT interacts with GAMS and other modules via shared memory. Internally, plant model interacts with automation (controller) system using virtual controller interface. (Both are inbuilt interfaces in SIMIT)
Brief Description of Operational Options	**What are the important operational modes/options for the module?** ○ SIMIT model can be run at various speed in the range of 25 % to 500 % than real time. **How are the selected and controlled?** ○ Once simulation started, various speed option can be selected using a drop down option available at the top of simulation window
General Directions to Apply to a New Problem	**What are the steps to tailoring this module to another use case?** ○ SIMIT is a generic platform with inbuilt libraries to model various commonly used components in the process industries. It also has a capability to design user specific components. Thus, one can use the platform to model any plant. However, the model provided in this project is specific to a test problem. Thus modification is limited to change of certain parameters that impact size of the plant (e.g., volume of the rector). These parameters can be modified by clicking on particular component once the model is opened in the SIMIT platform. Behavior of the user defined components also can be changed by modifying their source codes. Source code of the user defined components can be accessed on double clicking on the particular component. Note: In order to make these changes licenses mentioned earlier are required.

MEO Executive Program	
Brief Description / Purpose	**What is this component?** A purpose built Python program **What is its purpose?** To provide a communication medium and workflow between critical modules which have no direct method of communicating with each other. **How does it perform its purpose?** It communicates to and from the SIMIT simulation platform using a shared memory space. Communication with other modules Scheduling Model (GAMS) and the Delay Prediction Module are done using text files. Workflow is controlled by continuously looping through a sequence of subroutine calls and file manipulations to carry out the MEO operations, while reporting errors.
System Requirements	**Hardware requirements** The project was developed on a Lenovo W541 laptop. **Operating system requirements** These components were developed on Windows 7 64 bit. **Software dependencies (solvers, libraries, etc.)** Anaconda Python 2.7. **Licenses required** None

Input and Communication Medium	**What does it use as input information and data?** Program behavior is configured using a user modifiable file called parameters.yaml. The parameters in this file are fully documented in the MEO program manual. **How is this input passed to this module?** Modules executed from within the Executive Program communicate together using text files. The text files' specifics are documented fully in the MEO program manual.
Output and Communication Medium	**What does it generate as output information and data?** Important files such as detailed reports from GAMS and imaged from the visualization module are generated during each loop of the executive program. The program also generates a dynamic Gantt chart of the schedule. Visualizations such as the GANTT chart are displayed on screen while the program runs. Process information and diagrams while not provided by the Executive Program can be viewed within the Siemens SIMIT program which should be running alongside the Executive Program. **How is output made available?** ○ Files and images are saved into a folder ○ Each Gantt chart is saved into a folder created for the scenario.
Brief Description of Operational Options	**What are the important operational modes/options for the module?** Behavior of the Executive Program can be modified via input parameters (parameters.yaml). **How are the selected and controlled?** Individual modules can be disabled for testing/debugging purposes by setting parameters such as simulate_gams which would then in a very basic way simulate the way that GAMS is supposed to run. The GAMS models called during normal operation and the startup routine can be defined (more than one can be called in series) from within the parameters as well.
General Directions to Apply to a New Problem	**What are the steps to tailoring this module to another use case?** For new applications that use the SIMIT simulation platform for simulating the process, no reprogramming is needed. If SIMIT is replaced by another simulation platform or an operating control system then the communication routine to receive/send data to the process needs to be reprogrammed.

III. ACCESSING THE TECHNOLOGY

Our MEO solution framework is derived from recent developments in the fields of optimal production scheduling using the Resource Tasks Network (RTN), discrete event systems for formal design and analysis of automation logic using the model checking solver NuSMV, data analytics for extracting predictive models from historical process data using latent variable methods, and real time optimization currently applied to continuous processes in the petro-chemical industry. The background intellectual property associated with our deliverables is listed below.

Deliverables (All forms of Project IP)	BIP Required (If Any)	Approximate Cost of BIP to DMDII Members
Multi-variable statistical models	Appropriate modeling software	Varies by license
Integrated RTN-based scheduling-automation model	Computerized System for Chemical Production Scheduling (US2014/0031963 A1)	Capped at $25,000 per license. Negotiable fee depending on use (educational or manufacturing).
Delay Monitoring and Prediction module (DMP)	st2smv and SynthSMV: developed by Blake C. Rawlings during his Ph.D. project	$0 (open source,)
SIMIT model of test process	Siemens SIMIT simulation platform	$25,000 for a full SIMIT license
MEO Executive Program	None (built in Python)	$0
MEO solution in simulation framework applied to test problem	Per the components listed above	Per the components listed above
Visualization module	None (built in Python)	$0

VI. INDUSTRY IMPACT & POTENTIAL

The project described here addressed the lack of a commercial platform for real time optimization of batch processes, as well as short term campaigning on roll-to-roll processes. These processes are used to produce a suite of valuable, high-grade products. Their economic performance is highly dependent on the quality of production planning and scheduling that directs their overall operation, and the fidelity by which these plans are carried out in the manufacturing process. Commercially available planning and scheduling software, while capable of developing schedules using sophisticated algorithms, rely on human intervention for execution of production schedules, as well as monitoring the process to respond to circumstances that would require reworking schedules to keep them feasible. The lack of the integration of production scheduling with the process control system represents a significant manufacturing capability gap in achieving real-time optimization of batch processes. The Manufacturing Execution Optimization system developed in this project fills this gap by providing an early stage platform for investigating and deploying a solution applicable to many industries.

The market impact of the MEO system is two-fold. It can provide improved asset utilization in the manufacture of specialty products like pharmaceuticals, fine chemicals, and advanced materials to name a few. It can also be integrated into existing commercial process control platforms to provide value added enhancements. Considering just the U.S. pharmaceutical industry which in 2014 experienced total sales of $333 billion (1.9% of GDP; 10.7% of total healthcare exp.) and the 5% increase in manufacturing capacity Dow has demonstrated using online scheduling models, the potential economic impact of widespread use of MEO methods is enormous.

VII. TECH TRANSITION PLAN & COMMERCIALIZATION

All team members believe the project has produced meaningful results for their respective organizations and they are considering the following future plans:

University of Wisconsin
- Investigate methods to add more automation logic to the scheduling model
- Use the Simit simulation platform to provide a realistic testbed for research

Siemens
- Investigate commercialization with internal business units
- Work with Dow on application of MEO on Dow plants using Siemens control systems

University of Michigan
- Investigate adding reduced discrete logic to the scheduling model
- Extend methods so they can extract logic from forms of automation coding other than structured text

Kent Displays
- Improved campaign planner for a larger number of products

The Dow Chemical Company
- Apply MEO to additional businesses in Dow

While Dow will launch projects to implement the MEO system in selected manufacturing operations the project team sees two barriers to widespread adoption:

- Tailoring the MEO solution to another manufacturing process and its control system requires subject matter experts
- The MEO platform is not commercial grade software

VIII. WORKFORCE DEVELOPMENT

Kent Displays, the project partner organization with the least experience in factory optimization, developed the workforce development initiative aligned to the project. The goal for the initiative is an evergreen pool of talent for shop floor line operators trained in factory optimization. The initiative is designed to address root causes for the small number of qualified candidates. Root causes are the lack of knowledge candidates have about Kent Displays and the field of manufacturing. Based on raising public awareness about jobs in manufacturing and specifically in Kent Displays, the initiative seeks to set up a talent pipeline.

Kent Display’s approach to talent pipeline management is inspired by the U.S. Chamber of Commerce Foundation Talent Pipeline Management™ initiative started in 2014. This innovative initiative is designed to mobilize the business community to close the skills gap by applying methods from supply chain management to its education and workforce partnerships. The idea is that if employers play an expanded leadership role as “end-customers” of a talent supply chain, they will be more effective at organizing performance-driven partnerships with responsive preferred education and workforce training providers.

Kent Displays views workforce development as a long term investment. Their workforce development initiative contains the following elements:

- Manufacturing Day Events- Hosting annual event with local Kent middle school to raise awareness of Advanced Manufacturing
- Explorer Post- Establishing Science of Manufacturing Post to provide in depth introduction to teens and to evaluate them as potential employees before hiring.
- Stark State College Employer Partnership Program- Provides access to student talent pool at job fairs and recruiting events, access to a database of student resumes, special promotion of open positions and invitations to campus to interview students.
- Apprenticeship- Investigating state recognized apprenticeships for Factory Line Workers based on MSSC for Certified Production Technician
- Pairing education attainment to career positions as shown in the following table

Education	Career Position
High School	General Laborer
Pre-Apprenticeship	Skilled Worker
Apprenticeship	High Skilled Worker
Community College	Supervisor
Four Year College	Operations
Advanced Degree	Operations Leadership

IX. CONCLUSIONS/RECOMMENDATIONS

We have shown that knowledge of the automation system's dynamics in a chemical plant can be incorporated in the rescheduling problem to improve the quality of the closed-loop scheduling compared to simple periodic rescheduling. This is an early step toward bridging the gap between the detailed models used when analyzing automation systems and the higher-level models of the plant's operations used in a typical scheduling problem. We demonstrated this approach with a test case involving a batch reactor reliant on manual interventions by a process operator producing multiple products. The entire closed loop Manufacturing Execution Optimization system can be adapted to other use cases and modified for implementation on operating manufacturing processes.

We further have shown that the methods of MEO system can be simplified for offline application and put to use on the manufacturing line at Kent Displays. We were able to establish ongoing use of these solutions for the benefit of the KDI.

Based on all the results we obtained from our testing regime of the MEO system and the application of the solutions for Kent Displays we report the following conclusions and recommendations:

- The MEO solution
    - Improves schedule performance in real time by appropriately responding to delay events in the system
    - Has the following limitations:

        - Application is best suited for batch processes and discrete part manufacturing
        - The methods as developed are limited to moderate size problems
    - Will be implemented within Dow’s environment
    - Delay monitoring and prediction module can be applied with a manually derived production schedule to provide improved visibility to process operators
    - There would be value in implementing the system at a DMDII testbed for additional experimentation and validation of its general purpose nature
    - Should be explored for implementation in Simatic IT
    - Explore data driven methods to predict scheduling delays
- Tailored solutions for Kent Displays
    - KDI have benefited and will continue to use the solutions
    - KDI should explore advanced image classification of their raw material rolls
    - KDI should extend the capability of the campaign planner for more products
- Workforce Development:
    - Find internal workforce development champion(s)
    - Pick one position and one national certification program
    - Engage local and regional ecosystem partners
    - Build a pipeline model that addresses local needs
    - Fit partners into pipeline
    - Expect the need to test and adapt the approach

X. LESSONS LEARNED

The main problems encountered during the project are listed in the table below along with the mitigation steps taken to overcome them.

Problem	Impact to Project	Mitigation Plan
Scope of the original test case was too large to be addressed in a 12 month project	Demonstration of results were limited to a smaller problem	Focus development on a single batch reactor test case which exhibits the important features of the original test case that needed to be addressed
The importance of capturing the field operator’s decision framework in the Delay Monitoring and Prediction Module was not anticipated at the outset of the project	Required the team to develop a method that was not part of the original proposal	Focus the application of discrete event systems to the development of the online monitoring (DMP) and forgo the development of the reduced discrete logic for the scheduling model.
Integration of software modules developed in parallel by 4 organizations required significant alignment of communication protocols, data definitions, and control parameters.	Development time for integration took more time than anticipated	Virtual working meetings were held twice a week to overcome the technical challenges. Fewer test scenarios were performed.

Lessons learned by the project team can be summarized as follows.

- More specific performance specifications for the project would have helped to drive development
- The project should have put more emphasis on integration rather than innovation
- Working meetings were critical but should have started earlier in the project
- One year project is difficult for academic resources
- More members of the team should have been responsible for scenario testing and debugging
- A dedicated, professional project manager would have been very helpful
- The initial uncertainty on external release of material made it hard for team members to plan accordingly
- Gitlab was very useful as a platform to store and share software developments
- The responsiveness of team member was crucial to success
- Simplifying the scope and outcomes key to success
- DMDII program managers were very helpful
- The teamwork exhibited during the project was a key to success