Toward Smart Manufacturing Using Decision Analytics

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Outline

- **Key Contributions:** Decision Guidance and Analytics for Buffered Temporal Flow Processes (BTFP)
- **Problem by Example:** Monitoring, Analysis, Planning and Execution of Smart Manufacturing BTFP
- **Challenge:** from Existing Technologies to Decision-Guidance Analytics (DGA)
- **Solution:**
  - DGA Framework
  - DGA models for base components and process composition
  - User-defined composition of BTFP Processes
  - Monitoring
  - Analysis
  - Planning (Process Optimization) and Execution
- **Conclusions and Future Work**
Scope and Key Contributions

- **Consider Manufacturing Processes**: composite, over sequence of time intervals, with stochastic throughput and work-in-process buffers.
- **Use recently proposed Decision-Guidance Analytics (DGA) framework to model**:
  - generic DGA module of process flows, inventory aggregators, base throughput machines and process composition
  - domain-specific process models for a simple demonstration example of a manufacturing process
  - domain-specific module for analytical view points for monitoring, analysis and planning (process optimization) for the demonstration example
- **Demonstrate reusability and ease of use of declarative **DGA queries** against library modules to perform**:
  - monitoring (aggregated power consumption vs. expected bounds)
  - analysis (learning coefficients of machine models)
  - planning (optimizing setting of machines and load distribution to minimize cost while satisfying demand over time)
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Problem by Example:

Buffered Temporal Flow Processes (BTFP):

• hierarchical composition
• temporal: over sequence of time intervals
• atomic processes = machines
• stochastic
• work-in-process buffers
• process control = machine setting, load distribution etc.
• metrics (cost, energy etc.) are functions by process control
• process output (produced products) and input (consumed materials/parts) are functions of process control
• process constraints = machine capacity, zero-sum-flow, material-to-product ratios etc.
Problem by Example (cont.)

Monitoring, e.g.:
• process streams of sensor and meter data from multiple sources
• clean, filter and pre-process raw data
• aggregate metrics by time/machine/process/product ... dimensions to present & visualize for process operators
• compute predicted metrics and their bounds to be compared with observed metrics
• visualize performance graphs (observed vs. predicted) to help operators with diagnostics
Problem by Example (cont.)

Analysis (regression, classification, what-if predictions, diagnostics), e.g.:

• model/parameter calibration, e.g., for a machine: given history stream of machine setting (e.g., throughput) and metric (e.g., consumed power), find coefficients of a piece-wise-linear function for power

• model-based diagnostics, based on capturing statistically significant deviation of observed behavior (e.g., power of machine or inventory buffer level) from the predicted behavior

• fault-based diagnostics by learning classifiers of machines’ faults (given a supervised parametric fault model)

Planning (process optimization, what-if sensitivity analysis), e.g.:

• Given the demand for output products over time, determine setting of machines and load distribution at each time interval to minimize total energy consumption while satisfying demand (over time) with probability $\geq 99\%$.

Execution, e.g.:

• data transformation of the recommendations from the planning phase into machine controllers (via MES)
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**Challenge**: Soup of Technologies, each is good for some tasks but not good for others ...

- closed domain-specific tools
- integration/collaboration platforms + agent-based reasoning systems
- data manipulation languages: SQL, XQuery, JSONiq
- optimization modeling (OPL, AMPL, GAMS) + MP/CP Solvers
- statistical learning and data mining, e.g., using PMML
- simulation modeling e.g., Modelica, Jmodelica, Simulink, ...
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Diverse technologies
- require separate models of same processes (because of different abstraction / language)

- SPAF (sustainable process analytics formalism) developed at NIST unified simulation and optimization models (reusability/modularity of simulation models + efficiency of MP/CP optimization)
  - but is not designed for data manipulation, statistical learning and stochastic prediction
Challenge: from existing technologies to Decision Guidance Analytics

- conventional approach to implementing Description, Prediction and Prescription Analytics tasks is sequential, task-centric, and not reusable

- recently proposed Decision Guidance Analytics (DGA) framework is Analytical Knowledge-base centric, modular and reusable.
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Solution: Decision-Guidance Analytics framework

**Decision Guidance Analytics Language Knowledge Base**

<table>
<thead>
<tr>
<th>Construct/Compose AOs</th>
<th>Compute/Query/Predict/Assess AOs</th>
<th>Optimize/Satisfy AOs</th>
<th>Learn/Calibrate/Classify AOs</th>
</tr>
</thead>
<tbody>
<tr>
<td>base components &amp; process composition</td>
<td>views for monitoring, analysis, planning, execution</td>
<td>user-defined processes</td>
<td></td>
</tr>
</tbody>
</table>

Extensible Viewpoint (VP) Libraries of Analytical Objects (AO)  
(AO = data/params-vars/computation/constraints/uncertainty/...)

**Impl. Tools**
- DBMS
- Optimization (MP & CP) Solvers
- Queueing Solvers
- Simulation Modeling Tools
- Analytics/Statistical Learning Tools

...
Solution: DGA framework key features

- Reusable-KB-centric modeling approach
- Task-independent representation of analytical knowledge
- Unified language for analytical knowledge manipulation
- Flexible construction of analytical knowledge using data manipulation language JSONiq over the data-model JSON
- Declarative high-level language
- Ease of use by modelers and end-users
Solution: Generic DGA library of base BTFP models (written in JSONiq with annotations)

- metrics
- itemFlow
- inventoryAggregator
- inputAggregator
- outputAggregator
- processInterface
- baseProcess
- compositeProcess
Solution: Composing Processes

- JSONiq code that invokes CompositeProcess from DGA library and sets:
  - sub-processes
  - item flows, including input and output
  - inventory aggregators (incl. input and output aggregators)

- Can be automatically constructed by a visual tool (outside the scope of this paper)
Monitoring: observed vs. predicted

<table>
<thead>
<tr>
<th>tp</th>
<th>Kwh per time window</th>
<th>Prod per time window</th>
<th>Kwh per product</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>25.8</td>
<td>6</td>
<td>43.34</td>
</tr>
<tr>
<td>7</td>
<td>42.4</td>
<td>8</td>
<td>5.3</td>
</tr>
</tbody>
</table>
Analysis: prediction view

```
declare variable $ns:sandCuPredicView as aObject := ( let
    $currentTime := ... // must be greater than $timeWindow
    $timeWindow := ..., $probability := ..., $machineSetting := ..., $inventoryQty := ...,
    for $i in range($timeWindow, $currentTime) let ( $tp as index := {tp:$i},
        $globalSetting($tp) := $smg:globalSetting { replace $noPeriods:= $timeWindow, $periodLength := 1.0 },
        $predictedProcess($tp) as := $emp:sandCuProcess { let
            $globalSetting := $globalSetting($tp),
            for $ma in $sc:sandCuProcess.$subProcessIds, $currP in range($tp-$timeWindow, $tp),
                $ms in $machineSetting
                where $ma = $ms:machine & $currP = $ms:period replace ( $pvar((id:$ma)).$throughputExp((period:$currP)) := $ms:thru
            )
            for $ia in $sc:sandCuProcess.$inventoryAggrids, $i$q in $inventoryQty
                where $ia = $i$q:inventory & $tp-$timeWindow = $i$q:tp let ( $iavar((id:$ia)).$initInv := $i$q:qty
                    $averageEnergyPerProduct := sum( for $ma in $sc:sandCuProcess.$subProcessIds,
                        $currP in range($tp-$timeWindow, $tp)
                        $sc:process $iavar((id:$ma)).$energy((period:$currP)) / sum( for $currP in range($tp-$timeWindow, $tp)
                            $sc:process $iavar((id:$ma)).$outputFlow((d:cutwood)).$periodQty((period:$currP)),
                        $predictedMax as float := ?
                        $belowPredMax as constraint:=
                            prob(averageEnergyPerProduct => $predictedMax) <= $probability,
                        )
                    $optimizedEnergyMax($tp) := minimize({aObject: $predictedProcess($tp), objective: "predictedN" return tp: $tp.tp, maxKwhPerProduct: $optimizedEnergyMax.$predictedMax
                )
            )
```
Analysis: learning view for a machine (find PWL coefficients)

```
declare variable $ns:sand1LearningView as aObject := {
    let
        $ns:globalSetting as $smg:globalSetting := ..., 
        for $i in range(1, $ns:globalSetting.$noPeriods) let {
            $period as index := {period: $i},
            $ns:cost($period) := ..., $ns:energy($period) := ..., $ns:throughputControl($period) := ..., 
        },
        $error as float := sum($period in $periodIndex) ( 
            $energy($period) - $sc:sand1.$energyPWL($throughputControl($period))) ** 2 + 
            $cost($period) - $sc:sand1.$costPWL($throughputControl($period))) ** 2 
    },
    $learnedSand1 as $smg:process:=learn ({$Object: $sc:sand1, params:["coef...values"], 
        error: $error}), 
}
```
Planning: process optimization

\[
optimizedProcess ::= \text{minimize}\{ \begin{align*}
    &aObject: \$ns:sandCutSchedulingView, \\
    &objective: \text{Exp}(\text{sandCutProcess: totalCost})
\end{align*}\}
\]
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Directions for Future Work

• Developing systematic manufacturing machine and process libraries for various domain-specific viewpoints

• Implementation of the DGA framework via reduction algorithms from queries against analytical objects (process models) to specialized formal models of optimization and statistical learning

• Algorithms for stochastic BTTP optimization

• Developing graphical user interfaces for domain-specific languages based on DGA framework
Conclusions.

Questions ???

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