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Which variety is free? Discerning the impact of product variety in the process industry

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Abstract. In the pursuit of mass customization, it is a great challenge for companies to maintain mass production efficiencies while producing a wide range of products. This poses an even a greater challenge to process industry manufacturing systems which are built for high volume, low variety operations and which are sensitive to changes in process parameters. Many studies have been performed to quantify the impact of product variety on the efficiency of automotive assembly processes, but little work has been done to address process manufacturing systems. This study aims to determine the effects of individual product features on machine productivity at a process industry manufacturer. A lasso regression model is developed and tested using actual product and process level data from a stone wool manufacturer in central Europe. Results show that product features are less correlated to machine efficiency than process parameters, such as planning and crew performance.

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1 Introduction

On the path to mass customization (MC), meeting ever expanding customer needs in affordable ways becomes imperative for the manufacturing firm. Waves of MC, producing customized products at mass production efficiencies [1], have hit the automotive, electronics, and clothing industries but have yet to hit many manufacturers in the process industry. Process manufacturers typically utilize production systems with high capital investment [2] and complex process variables which make the systems sensitive to product variety required in MC. While companies can regain lost throughput from product variety by understanding production dynamics and enabling more accurate prediction of processing times and sequencing [4], there is an unexplored field combining existing methods with Big Data analysis to determine “which variety is free?” in process manufacturers [3]. The purpose of this paper is to address this gap by presenting a combined assessment of the impact of product features on production throughput (tons of saleable product per effective hour of the production line) at a process manufacturer using lasso regression.

2 Methodology and Preliminary Findings

This project uses lasso regression to approach the problem using data from a mineral wool insulation manufacturer in Europe producing over 400 products on a continuous flow production line. The insulation products can contain added features, such as fabric or aluminum adhered to one side, multiple densities, or wire woven into the product.

Qualitative data on the production process, production scheduling process and scheduling rules, and product features was gathered from the ERP system, product specification sheets, and semi-structured interviews with the following factory personnel: 1 manager, 1 process engineer, 4 product managers, 1 IT specialist, 2 production planners, 4 operators, and 1 quality manager. All personnel were interviewed once for 45 minutes, except for the factory manager and process engineer who were interviewed 4 times for 45 minutes. Eighteen candidates for independent variables affecting production throughput were identified through the interviews. Variables were separated into product and process variables in Tables 1 and 2, respectively.

Table 1. Product independent variables

Product / Process variable	Description of variable	Data Type	Data Source
Density	Structural parameter	Discrete	ERP
Height	Dimension	Discrete	ERP
Lambda	Thermal conductivity coefficient	Discrete	ERP
% Binder Content	Recipe parameter	Discrete	ERP
Fleece	Fabric applied to one side of product	Binary	Spec. sheet
Dual Density	1 if product has two densities, 0 otherwise	Binary	Spec. sheet
Galvanized Steel Mesh	Wire woven into product	Binary	Spec. sheet
Stainless Steel Mesh	Wire woven into product	Binary	Spec. sheet
Aluminum Foil	Foil applied to one side of product	Binary	Spec. sheet
Length	Dimension	Discrete	ERP
Width	Dimension	Discrete	ERP

Table 2. Process independent variables

Product / Process variable	Description of variable	Data Type	Data Source
Sequence	Indicates if runs are sequenced to minimize changeover waste	Binary	MES, Interviews
Run length	Run time excluding planned/unplanned stop orders	Continuous	MES
Double Batch	Indicates if product is the same as product in previous run	Binary	MES
Crew 1	Indicates crew 1	Binary	MES, Interviews
Crew 2	Indicates crew 2	Binary	MES, Interviews
Crew 3	Indicates crew 3	Binary	MES, Interviews
Crew 4	Indicates crew 4	Binary	MES, Interviews

Production run data from the manufacturing execution system (MES) for 2016 was the primary dataset. Data was cleaned of infeasible values due to data entry error (e.g. run length under 5 minutes), production stops, and outliers with an assignable cause (e.g. scrap over 20% of gross production). Since throughput of the line is determined by the bottleneck machine for each product, MES data was segmented by bottleneck groups.

Nine linear models, one per bottleneck group, were constructed using the 18 independent variables and dependent variable, production throughput. Models were solved using lasso regression to handle the high number of variables and potential multicollinearity [7]. The cost-function penalization parameter λ was found using inner, k-fold cross-validation where $k = 20$ for each bottleneck group model.

Preliminary results show that product features partially impact throughput. For example, adding aluminum foil to a product in bottleneck group 9 reduces throughput by 6%. In contrast, fleece is considered “free” variety since throughput does not reduce significantly for fleece products. Run length and sequence show the largest impact on throughput. This research will further develop to refine the model and recommend variety management initiatives.

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