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A material flow modelling tool for resource efficient production planning in multi-product manufacturing systems

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Abstract

Resource efficiency is recognized as one of the greatest sustainability challenges facing the manufacturing industry in the future. Materials are a resource of primary importance, making a significant contribution to the economic costs and environmental impacts of production. During the manufacturing phase the majority of resource efficiency initiatives and management methodologies have been concerned primarily with improvements measured on an economic basis. More recently, the need for even greater levels of resource efficiency has extended the scope of these initiatives to consider complete manufacturing and industrial systems at an economic and environmental level. The flow of materials at each system level relates directly to material efficiency, which in turn influences the consumption of other resources such as water and energy. Initial research by the authors in material efficiency focused on material flow, proposing a material flow assessment approach, comprising a systematic framework for the analysis of quantitative and qualitative flow in manufacturing systems. The framework was designed to provide greater understanding of material flow through identification of strengths, weaknesses, constraints and opportunities for improvement, facilitating the implementation of improvement measures for greater efficiency in both environmental and economic terms. This paper presents an extension of this work, applying the material flow assessment framework to a complex multi-product and multi-site manufacturing system scenario. It begins with a description of the Resource Efficient Scheduling (RES) tool that supports the implementation of this framework. The tool models the interactions of quantitative and qualitative material flow factors associated with production planning and the resulting impacts on resource efficiency. This provides a more detailed understanding of the economic and resource impacts of different production plans, enabling greater flexibility and the ability to make better informed decisions. Finally a case study is presented, highlighting the application of the tool and its potential benefits.

Keywords: Sustainable development; Manufacturing; Resource efficiency; Material flow; Production; Planning; Modelling;

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1. Introduction

Increasing global demand for and decreasing availability of resources is a concern for the future of manufacturing. There is a growing realization that the current unsustainable trajectory of resource consumption is far from being diminished. Accordingly, there is significant interest in facilitating more efficient and sustainable use of the key manufacturing resources: materials, water and energy. Whilst the concept of resource efficient manufacturing (REM) is not new to academia or much of industry, it has mainly been pursued as a means to improving economic performance of the business [1]. Nevertheless, REM is readily compatible with the goals of sustainable development in manufacturing, where resource conservation and minimization of environmental impacts, along with associated social and economic benefits are the joint focus.

Although there is a large body of literature relevant to improving resource efficiency, it is predominantly concerned with incremental improvements of individual technologies or processes within a specific application. There is a need for methodologies and tools that support manufacturer's decision

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making to radically and holistically enhance resource efficiency for more sustainable design of products, processes and production systems.

In terms of the sustainable design and operation of production systems, research into the flow of water, energy and materials is a relatively new area of research. Previous work has developed methodologies and tools for examining manufacturing systems using simulation modelling to identify opportunities for energy [2] and water [3] conservation. Materials may be considered as the dominant resource consumed in the majority of manufacturing applications, both in terms of the amount and economic cost [4]. Despite this, material flows through a factory are often poorly understood and identifying opportunities for improving efficiency is difficult. Material flow has inherent complexity due to the diverse qualitative and quantitative aspects related to materials as they move and transform within processes over time.

Furthermore, the flow of materials in manufacturing, in terms of the materials used and processes applied, is often the principle factor influencing water [4] and energy [5,6] consumption both within the factory and also from a life cycle perspective. Indeed, energy consumption is often used as a proxy for measuring environmental performance associated with the selection of materials and processes acting upon them [7]. Better understanding of material flow can therefore be seen as the underpinning to resource efficient manufacturing.

There are various ways to manipulate the material flow in a manufacturing systems to influence resource efficiency: from the design of products (selection of materials, amounts required, geometries), to the design of processes (selection of diverse material transformation, transport and storage processes), the design and operation of production systems (including the layout, connectivity of processes and scheduling of activities within a factory) and enterprises (multi-site operations).

Manufacturing scheduling has in the past predominantly been carried out based on performance indicators such as cost and cycle time. In material flow terms, production scheduling (the temporal material flow) can be an important factor impacting the consumption of other resources (materials, energy and water). Until recently, the environmental impacts related to material flow in this sense have not been investigated thoroughly.

Early investigations evaluated machining operations using a holistic environmental impact analysis approach, for more ‘environmentally conscious’ process planning [8,9]. More recent research has developed methods to minimize the energy consumption for one- [10] or two- machine [11] systems, focusing on the energy requirement during process operation. Significant past research has investigated computational methods for optimized process planning [12], including some involving optimization for energy consumption [13], although the majority of these studies have focused on manufacturing involving machining processes. Relatively little work has been done to provide practical tools for manufacturing process planning and scheduling for improved resource efficiency in manufacturing systems in general. A greater focus on modelling material flow in dynamic manufacturing systems is likely to be key to improving material efficiency and resource efficiency overall in this context.

Previous work by the authors provided a systematic way of assessing material flow and constructing dynamic models representative of manufacturing systems, by encompassing qualitative and quantitative information to better understand how a system operates and how material efficiency might be improved [14]. This was developed with a view to (amongst other aspects) providing a basis for measuring energy and water flow as variables influenced (directly or indirectly) by material flow, thus enabling an understanding of the interactions between different resources to balance variables and deliver a global optimum.

In this paper we describe an application of the previously described framework for material flow assessment in manufacturing systems (MFAM) [14] to examining a complex multi-product manufacturing system scenario. Also described is the development and application of a Resource Efficient Scheduling (RES) tool, used in the fourth phase of the MFAM framework to optimize material flow for minimized resource consumption.

2. Method

2.1. Framework implementation

The manufacturing system used for a case study was a single site facility encompassing over 1000 different finished products on 2 production lines, using more than 1000 different raw materials.

The MFAM framework was used to systematically analyze and model the manufacturing system in five separate phases (highlighted in Fig. 1), incorporating: production system scope definition, material flow inventory, a material flow assessment, improvement scenario modelling and interpretation. The ‘interpretation’ phase is designated as the fifth phase; however, is intended to be a continuous reflective process, allowing for iterations of the phases to allow for flexibility in assessment, ultimately facilitating the construction of a representative model providing relevant results and recommendations.

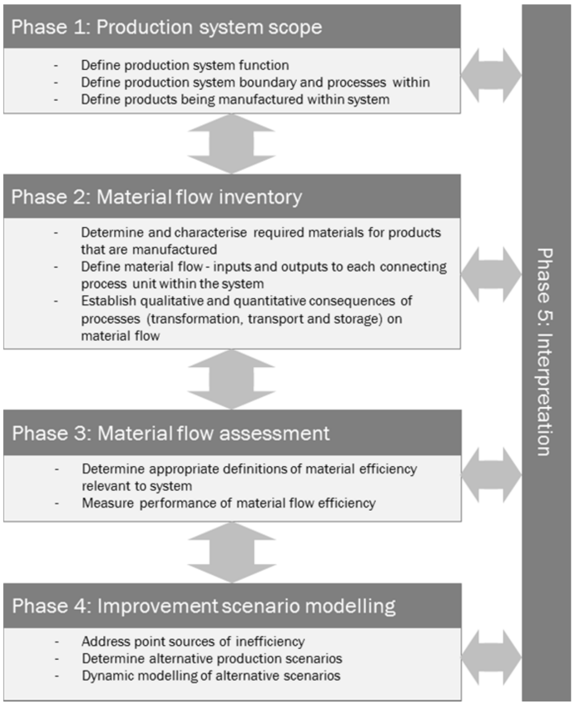

Fig. 1. Five phases of the framework for material flow assessment in manufacturing (MFAM) from Gould and Colwill (2015)[14].

2.2. Phase 1: Production system scope

The purpose of the assessment was to examine and explore options to improve the resource efficiency of a production system. These options could include suggested alterations to the system design and how it operated. Changes to the design and specification of products were out of scope.

The function of the production system was identified broadly: to produce a large range of products to orders of various sizes, using relatively few processes on 2 production lines. The spatial boundary included the production lines contained in a single building. The temporal boundary was set to include information over a timescale relating to orders received for multiple products (i.e. 20 different products could be required, of 100 units each, the temporal boundary would be the time taken to complete the order, i.e. 2000 units). The product boundaries were set according to the applicable spatial boundary of processes required, i.e. products were divided into subsets according to their corresponding production lines.

The key transformation processes were material combinations, including a material mixing process (uniform distribution of materials) followed by two packaging processes: individual packaging of material mix doses and subsequent multi-product packaging. A number of material transportation and material storage processes were also included. Fig. 2 shows an input-output diagram illustrating the processes included in a single production line.

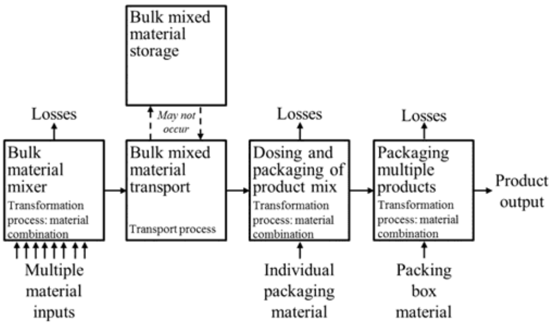

Fig. 2. Input-output schematic of processes contained within a single production line. Processes are shown as boxes, descriptions inside. Material flows (black arrows) are variable depending on product. Dotted arrow (to storage of bulk material mix) indicates that a material flow may be zero.

2.3. Phase 2: Material flow inventory

The complexity of the system was mainly due to the large range of products and the large range of different raw materials making up each product. The range of products was divided into subsets according to their corresponding production lines. Initial investigation of material losses indicated the occurrence of relatively frequent, very minor losses due to small spillages. It was decided that these losses were not to be the focus of analysis as the scope for material efficiency improvement was limited. Infrequent significant losses (reject products) also occurred, mainly due to operator errors in processing (e.g. incorrect product packaging used or incorrect materials added to mixing process). This represents potential opportunity for improvement, for example, by introducing increased automation, inspection points, checks or inventory control procedures. Alternative process design may also eliminate possibility of operator errors. Further analysis of these opportunities was warranted.

The transformation processes (bulk mixing) did not alter these physical characteristics significantly, however the process was not reversible; it was not practically feasible to separate constituent materials for reuse. Thus any process waste material (spills etc.) was not recoverable; however, there was scope for recovering mixed materials from incorrectly packaged products.

An important qualitative feature of many of the materials in the inventory was that they were a potentially hazardous contaminant if carried over between different products from one production run to the next. These materials were categorized into multiple different types of potentially cross contaminating materials (PCCM). To avoid cross contamination of these materials between different production runs, where different products had different amounts of PCCM specified, a strict changeover protocol had been designed for cleaning the entire production line. This changeover protocol defined the level of cleaning intensity required between products to reduce the concentration of PCCM within processing equipment to below threshold levels, based on the concentration of materials contained in the preceding and following unit product. There were three different variations of cleaning process (short, medium and long clean) and the resources (time, water, auxiliary materials and energy) required for each of these was markedly different, increasing significantly from short, to medium, to the long clean protocol. The material flow of PCCM embedded within the different products with respect to time was a particularly important direct influence on the resource consumption associated with the production line.

2.4. Phase 3: Material flow assessment

Based on findings from the previous phases, the focus for assessment of material flow was the resource consumption associated with product changeovers. For this initial analysis, production yield was assumed to be near-ideal (i.e. no significant yield loss) and constant during production.

2.5. Phase 4: Improvement scenario modelling

The improvement scenario was based on the assumption that for a required number of different products, the sequence of production could be optimized for minimal cumulative resource consumption during changeovers. The RES optimization tool was developed based on the modelling boundaries and criteria determined in the first 3 phases, to simulate production scenarios and generate optimized suggestions. The cumulative changeover time required (which includes water, energy and other overheads) was used as a proxy for overall resource consumption in the initial analysis. Finding the optimal sequence of products with minimized resource consumption was determined to be analogous to the asymmetric travelling salesman problem (ATSP), where each product was represented by a node and the ‘distance travelled’ between nodes was represented by the changeover cleaning time. Expedient solving of the ATSP in this context was approached using a genetic algorithm (GA) [15], a concept first developed by John Holland [15] enabling the determination of a near optimal solution of complex problems (e.g. NP-hard problems), using feasible computing resources.

GA has previously been applied to various flow-shop scheduling problems [16]. In this paper, the performance of the GA, in terms of computation time taken to provide a ‘near optimal’ sequence of products, was compared to that of a ‘brute-force’ comprehensive search algorithm, which, in contrast to the GA, provided every possible combination of product sequence with corresponding cumulative cleaning time.

2.6. Phase 5: Interpretation

Whilst being a continuous and iterative process throughout the phases, findings and interpretation of results based on the scheduling tool are presented in the following sections of this paper.

3. Modelling: data collection and processing

3.1. Product inventory, selection and PCCM

A random selection of 50 products was made from the product inventory. The content of each PCCM in each product was designated according to content levels 0, 1, 2, and 3. The changeover cleaning protocols, defined by the PCCM content of the former and latter product in a scheduled sequence, is defined in Table 1.

Table 1. Logic rules for product changeover cleaning requirements.

PCCM content level		Changeover
Former	Latter	cleaning requirement
0	0	Short
0	1	Short
0	2	Short
0	3	Short
1	0	Short
1	1	Short
1	2	Short
1	3	Short
2	0	Medium
2	1	Short
2	2	Short
2	3	Short
3	0	Long
3	1	Short
3	2	Short
3	3	Short

The cleaning procedure required is indicated by the greatest decrease in PCCM content from the former to latter product, across each of the categories. In other words, the most (time) intensive cleaning process indicated is the one selected (order of intensity is long > medium > short clean). Two of the PCCM had special rules adopted in addition to those reported in Table 1; if the former product contains any amount of these materials (level 1, 2 or 3) and the latter product does not (level 0), then a long clean is required. Otherwise, the normal logic rules apply.

3.2. Source-destination matrix determination

A source-destination matrix was calculated (shown in Fig. 3), describing the changeover cleaning required for each possible changeover pair within the product selection.

4. Decision support tool

4.1. Comprehensive search algorithm

To enable decision support for RES, a comprehensive search algorithm (CSA) was written to find the optimum product sequence based on minimized cleaning time, the steps for this are as follows:

1. Define number and PCCM data for products required
2. Calculate all possible product sequence permutations
3. Calculate cleaning time for changeover product pairs
4. Sum the cleaning time for sequence permutations

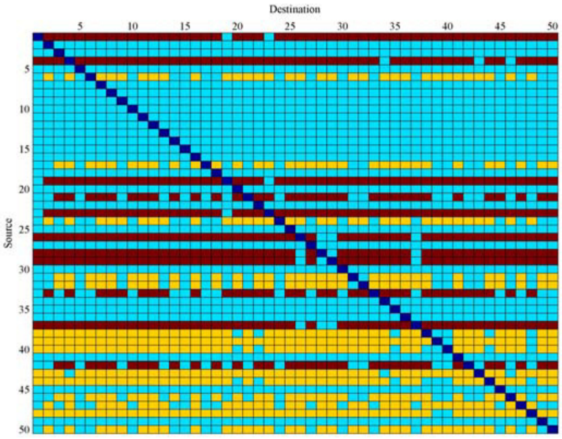

Fig. 3. Product source-destination matrix showing cleaning process requirement for all changeover pairs. 🟦 N/A, 🟦 Short, 🟨 Medium, 🟥 Long

This algorithm calculates all possible product sequences, with total cleaning times for each sequence. The minimum time may be given by multiple sequences, giving options for scheduling that may be prioritized using additional selection criteria.

4.2. Genetic algorithm

The GA procedure for solving the ATSP used the following steps [17]:

1. Create initial population of P (number of products) chromosomes (sequence), the initial product sequence (generation 0)
2. Evaluate fitness (i.e. total changeover time) of each chromosome (product sequence)
3. Select P parents from the current population *via* proportional selection (i.e., the selection probability is proportional to the fitness)
4. Choose at random a pair of parents for mating. Exchange bit strings with the one-point crossover to create two offspring
5. Process each offspring by the mutation operator and insert the resulting offspring in the new population
6. Repeat steps 4 and 5 until all parents are selected and mated (P offspring are created)
7. Replace the old population of chromosomes with the new one
8. Evaluate the fitness of each chromosome in the new population
9. Go back to step 3 if the number of generations is less than some upper bound. Otherwise, the final result is the best chromosome created during the search.

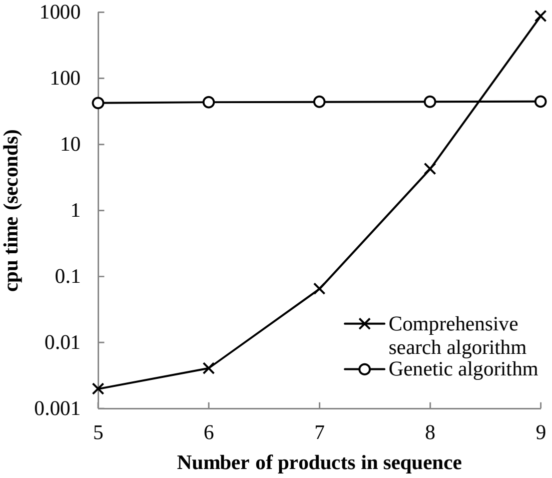

Fig. 4. Computing time required by comprehensive search algorithm and genetic algorithm to find optimal product sequence according to number of products

The following parameters were set up for GA, taking into account the results obtained against the computing time:

- P-by-P elements Source-Destination Matrix
- Population size = 100
- Number of iterations = 15000

4.3. Sequence optimization results

4.3.1. Comparison of comprehensive search and genetic algorithm

The CSA and GA were compared according to the optimisation time required as product number increased, starting with 5 products (Fig. 4). The CSA provided all possible sequences (finding the optimum), but becomes infeasible in terms of computation time for product sequences greater than 10. GA was slower for sequences less than 9 products but was significantly faster as sequences lengthened. Furthermore, time required for GA increased linearly, *ca*. 1 sec per additional product; therefore, the full inventory of products could be sequenced in reasonable time. This indicates good potential of the developed algorithm to provide optimized sequences for large numbers of product variants.

4.3.2. Sequence optimization for 50 products

GA calculated an optimal sequence for 50 products with the minimum changeover cleaning time requirement. The sequence is presented in Fig. 5, showing the changeover cleaning requirement per product pair. A short clean was required in all but 2 changeovers, where a long clean was required. Repeat implementation of the GA provides alternative product sequences with equivalent total cleaning time (data not shown). In this way, a selection of optimum sequences may be provided, which can then be prioritized with additional selection criteria.

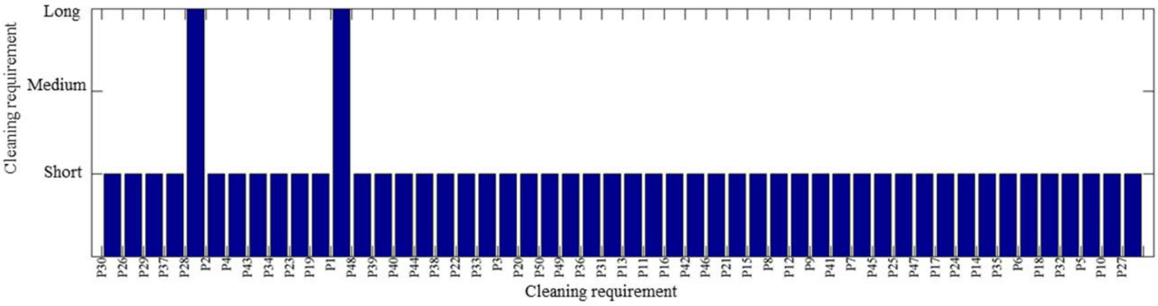

Fig. 5. Graph showing optimum product sequence for 50 products (P1 to P50) determined by genetic algorithm, showing the changeover cleaning between product pairs.

5. Conclusions and further work

A material flow assessment of a multi-product manufacturing system was carried out, highlighting key aspects of qualitative material flow and their implications for resource efficiency. Based on the findings, an optimization tool was developed to give decision support for improving material flow and resource efficiency through optimized product scheduling. The applicability and performance of GA was compared to a comprehensive search algorithm, indicating that GA would be preferred for sequences of 9 products or longer. It is likely that GA will be appropriate for application as further development and greater complexity is incorporated in the RES optimization tool.

Further iterations of the MFA will include more detailed examination of quantitative material flow, specifically to include production rates (material flow rates), so that the boundary is expanded to include order quantities and fulfillment requirements. This will be built into the existing RES tool for optimized product sequencing, with greater relevance to the real world system. In addition, agility in finding optimized sequences would be required; for example, orders for products may be received requiring a short lead-time (late notice, quick turnaround orders), therefore updated optimization, mid-sequence. Further development of this work will look to optimize sequences based on multi-parameter assessment, balancing water, material and energy consumption and impacts.

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