Scheduling and Batching in Multi-Site Flexible Flow Shop Environments

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Abstract —Global competition and the customers demand for customized products with shorter due dates, marked the introduction of the Extended Enterprise. In this Extended Manufacturing Environment (EME), lean, virtual, networked and distributed enterprises collaborate to respond to the market demands. In this paper we study the influence of the batch size on Flexible Flow Shop makespan minimization problem $FF_C||C_{max}$ for two multi-sites approaches, the FSBF (Flow Shop Based Factories) and the PMBF (Parallel-Machines Based Factories). The computational study demonstrates how the performance of the PMBF model decreases with the increase of batch size and determines the batch sizes in which the performance is similar.

Keywords - Extended Manufacturing Environment; Flow Shop Based Factories; Parallel-Machines Based Factories; Multi-Site Flexible Flow Shop; Batching.

I. INTRODUCTION

New production concepts, such as the Extended Manufacturing Environment and the Virtual and Networked Enterprises, have appeared in response to the dynamic marketplace. In this business environment the decision making processes became much more complex, as network manufacturers need to coordinate their production schedule. Nowadays, distributed scheduling problems have gained much as multi-site production and popularity networked manufacturing environments were introduced. Scheduling can be defined as the decision making process that adds the final detail to released orders. It can be divided in two main phases: allocation, which distributes production between the available resources in order to maximize performance; sequencing, which determines in which schedule/sequence tasks should be processed to maximize performance [1].

In the Extended Enterprise, schedule boundaries are hard to define. Manufacturers need to coordinate their schedule plans, since they can have an impact that reaches beyond the classical enterprise. On this Multi-Site model, production flows across networked enterprises and decisions made earlier in the production chain can have impact on the overall performance. On the Extended Enterprise context there are two alternative approaches to the schedule process, those build to deal with schedule process in the Extended Enterprise context and more classical and simple schedule approaches that are adapted for the Virtual and Networked Enterprise context [3]. ^{,4}H. M. Emrul Kays, ⁵A.N.M. Karim
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In distributed Flexible Flow Shop machine environments the batching policies can have a severe impact in the overall performance of the system. Batch sizes determine the manner in which items flow across the distributed Flexible Flow Shops and the number of items that are delivered in each production run. In most real-world scenarios, in-production items move from enterprise to enterprise in batches, to reduce the transportation cost, while most researchers approach the problem as if items will move production chain individually.

In this paper we demonstrate how two approaches to the distributed Flexible Flow Shop problem are sensitive to the batch sizes. The FSBF (Flow Shop Based Factories) model approaches the problem with parallel flow shop factories while the PMBF (Parallel-Machines Based Factories) approaches the problem with two parallel-machines factories [2]. In the FSBF model there is no batching, as the model is constructed with several Single-Site production chains, while the PMBF is constituted by one Multi-Site production chain and the batch sizes can have severe impact in the model performance.

This paper is organized as follows: Section II defines scheduling problem in the Extended Enterprise context. Section III introduces several classical batch size techniques. Section IV describes the Flexible Flow Shop *makespan* minimization problem, $FF_C||C_{max}$, and two approaches to the problem: the FSBF model and the PMBF model. Section V demonstrates how the PMBS model is sensitive to the batch sizes. The computational study and the statistical analyses of results is presented in section VI. Finally, the paper presents some conclusions.

II. SCHEDULING IN NETWOKED ENVIRONMENTS

EMEs can be identified as an intricate manufacturing system where the complexities arise from the geographical distribution of the manufacturing resources and/or their autonomy, besides the underlying problem complexity itself. In a distributed networked manufacturing environment, an enterprise consists of a core equipment manufacturer that produces the product and is supported by supply chains of materials manufacturers and services [3].

A Networked Environment (NE) is a kind of manufacturing environment which is flourishing nowadays as the Agile/ Virtual Enterprise (A/VE) environments, where dynamically reconfigurable global networked organization, a networked enterprise, or a network of enterprises have shared information and/or knowledge, skills, core competencies, market and other resources and processes to meet a fast changing market window of opportunity [3]. Moreover, an A/VE organizational model can be defined in the context of Ubiquitous Manufacturing System (UMS) network, which is characterized by a market of resources intensively spread through a globally distributed market [3].

Many approaches to solve the problem of static scheduling are often impractical in real-world environments for example the one occurring in NE, and the near-optimal schedules with respect to the estimated data may become obsolete when they are released to the shop floor. Networked manufacturing environments can occur regarding its complexity, which can arise, for instance, in terms of dynamic scheduling models, which may address a significant number of real-time events and their effects in various manufacturing systems, such as: single machine systems, parallel machine systems, flow shops, job shops, and flexible manufacturing systems [4-6].

A number of researchers propose using Software Agents to model NEs, namely distributed manufacturing environments (DME) [7-9]. A DME can be modelled through a set of intelligent software agents that interact in the planning and executing processes, each one being assigned to different tasks and responsibilities. A system built upon a set of agents that interact this way is a multi-agent system (MAS). Lu & Wang [10] define it as: "A multi-agent system is a loosely coupled network of software agents that interact to solve problems that are beyond their individual capacities or knowledge."

In Varela *et al.* [11] a web based system for technologies integration for supporting distributed scheduling in a Virtual Enterprise, by combining a simulation-based approach, with the Hungarian algorithm, for solving job-shop scheduling problems is presented, in order to show how users can benefit from this technologies integration for supporting collaborative distributed or networked manufacturing scheduling. Moreover, dynamic scheduling also does occur in NE and has been solved using different kind of approaches and techniques, such as: heuristics, meta-heuristics, knowledge-based systems, fuzzy logic, neural networks, Petri nets, hybrid techniques, simulation, web-based decision support systems, multi-agent systems and other approaches and decision models [12-19].

III. BATCHING STRATEGIES

In the network production where several enterprises that cooperate respond to the marketplace demands, several factors should be taken into consideration. Multi-Site production can also impose additional costs into the production chain. As inproduction items move between partner enterprises, the supply chain complexity increases. The transportation cost increase, as there is constant flow of in-production items across a global production chain. Transportation costs can be divided into: fixed costs, such as equipment acquisition, facilities, maintenance and the overall administration; variable costs that include, fuel, labor, conditional maintenance, and the overall order handling. The volume of items to be transported can have an impact in the overall cost, as the fixed costs are spread over an increased number of items and decrease the per-item-cost [20]. Fig 1 shows the relation between volume and cost.

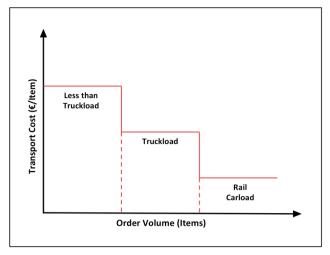


Figure 1. Order Volume / Tranportation Costs [20].

The transportation per-item-cost is related to the vehicleload minimum to better utilize the capacity of the equipment. Enterprises are incentivized to have their in-production items transported in bulk to benefit from the economies of scale. In this manner, the production chain will have fewer deliveries of bulk products, in order to minimize the transport prices, which constitute the main portion of the logistical costs, as fewer deliveries can translate into lower fuel, conditional maintenance, and processing and handling costs. Carload volumes present the minimal per-item-cost while less than truckload batches present the highest per-item-cost. Shipments that exceed the vehicle-load represent a cost that is identical, as seen in Fig. 1, as the fixed costs are spread over more items [20].

Fewer deliveries can have adverse impact in the production schedule. The transition between networked enterprises will need to be consolidated to minimize the transportation cost, what can have an impact in the makespan. In-production items that completed operations in one factory will have to wait for the rest of the batch to be transported to the next factory. This makespan-transport relation can be analyzed as an optimization problem, with two opposite objectives, the makespan minimization and the minimization of the transport cost of inproduction items. The minimal transport cost would be achieved with an increase in the batch sizes, to benefit from the scale economies as the fixed costs are spread over a large numbers of items, while the minimal makespan would be achieved with the reduction of the batch sizes to minimize the idle times of resources down the chain. The transportation costs are usually expressed in monetary units but it is often hard to quantify the monetary cost of an increase in the makespan, making this a hard problem to address with more traditional optimization methods.

In order to determine the batch size several other factors need to be taken into consideration. The storage costs will also be impacted by the batch sizes, larger batch sizes will impose higher storage costs, as items that are ready to be delivered need to be placed on storage while the rest of the batch is executed. Downstream factories will receive items in bulk, which need to be stored while they wait to be processed.

IV. FLEXIBLE FLOW SHOPS MODELS

Flexible Flow Shops are machine environments with c sequential work centres each with m equal machines. One of the machines at each work centre needs to execute each task, that need to flow sequentially over the work centres, from work centre c to work centre c+1 [1]. In the context of extended production models, flexible flow shops can be used to describe an industrial cluster where several production units collaborate to obtain the scale to remain competitive and still maintain a flexible, lean and nimble production schedule. This multi-site production presents schedule concerns that are unique to distributed flow shops, such as the batching procedure for the movement of in-production items between factories. Even if batching policies have been deeply studied, their application in extended production models can replicate more practical schedule concerns.

In this paper we give a contribution to the resolution of makespan optimization in flexible flow shops, $FF_C || C_{max}$, with two models detailed in [2], that limit the Flexible Slow Shop to two work centres in order to use the Johnson rule, each with variable number of parallel-machines. In the first model, the problem is based on the collaboration of several FSBF and the second in PMBF. Since the flexible flow shop models do not consider more than two work centres, the FSBF is limited to two successive machines factories and the PMBF is limited to two parallel machines factories, as seen in Fig. 2. An updated version of the models could consider more than two work centres with the use of the Slope heuristic [21,22], that is one of the best known heuristics developed for makespan optimization in permutation flow shops, $F_m | prmu | C_{max}$, or flow shops in which the execution sequence is maintained across all machines. In this case tasks are executed in accordance to the FIFO (First In First Out) methodology.

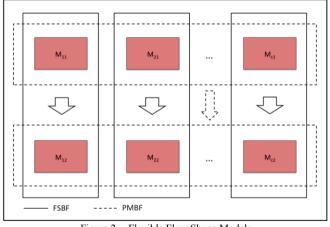


Figure 2. Flexible Flow Shops Models

For both models, FSBF and the PMBF, performances were evaluated with 40 instances [2]. In that comparison neither model used batching policies, which should be taken into account in practical schedule problems. A sensitivity analysis of the models performance with batching policies can demonstrate their feasibility in real scheduling problems.

A. FSBF Model

The FSBF model the $FF_2||C_{max}$ is modelled with several parallel flow shop based factories that collaborate to describe a flexible flow shop production environment. Even when this model is not an exact flexible flow shop, since tasks cannot move from one factory to another, it represents a common real-world scenario where several factories with similar production capabilities collaborate. In this case tasks are forced to move from machine M_{cm} to machine M_{c+1m} , which can impact the performance of the schedule model.

In the FSBF model there are two classes of decision makers, the GDM (*Global Decision Maker*) and the LDMs (*Local Decision Makers*). The GDM and the LDMs focus on separate parts of the flexible flow shop, each with different responsibilities. It is the GDM that maintains an overall perspective of the production system, which allocates production orders to each factory, as seen in Fig. 3. Each task is allocated according the LPT rule (*Longest Processing Time*), since it is assumed that factories are identical. The GDM reduces the flow shop to one operation and turns the parallel factories into a parallel-machines scheduling problem. Each LDM schedules operations within their factories, oblivious to operations that are allocated to other factories. Production will be scheduled in accordance with the Johnson rule, which is optimal for the $F_2 ||C_{max}$ problem in each factory.

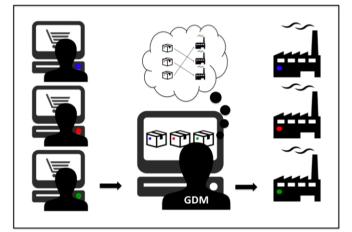


Figure 3. GDM in the FSBF Model

In the computational study, the FSBF was evaluated with 40 instances with a variable number of machines, tasks and two work centres. All the instances data were randomly generated from the numbers $\{0; 1; 2; 3; 4; 5; 6; 7; 8; 9\}$. FSBF mean deviation from best solution across all models was of 1.85 *t.u*, with a standard deviation of 1.889 [2]. These results can be explained by model characteristics that do not exactly replicate the flexible flow shop machine environment, since production cannot have parallel movement between factories, once allocated. Since in this model each task will be processed to completion in one of the factories, no batching policies were considered, what is not true for the PMBF model where the production is multi-site and batching policies should be considered for the movement of in-production items between factories.

B. PMBF Model

The PMBF model the $FF_2||C_{max}$ is modelled with two parallel-machines based factories that collaborate to describe a flexible flow shop production environment. In this model production flows across both factories, each responsible for one operation, that can be executed in one of the identical parallel-machines. Since in this model production can have parallel movements as it flows between factories, it replicates the flexible flow shop environment, unlike the FSBF that imposed some limitations to the production schedule.

In the PMBF model there are two classes of decision makers, the GDM (Global Decision Maker) and the LDMs (Local Decision Makers). The GDM and the LDMs focus on separate parts of the flexible flow shop, each with different responsibilities. It is the GDM that maintains an overall perspective of the production system, who sequences the production orders, as seen in Fig. 4. Tasks are sequenced with the Johnson rule. The GDM reduces the parallel machines factories into a flow shop schedule problem, since factories are identical. Each LDM allocates operations within their factories, which should be executed in the order determined by the GDM. Production orders are allocated in accordance with the RLPT (Released Longest Processing Time) a modified version of the LPT rule, where the longest processing time operation already released is allocated to the minimum completion time machine. LDMs will schedule the operations in a non-delay manner, as a machine cannot remain idle when there are release tasks to be processed [1].

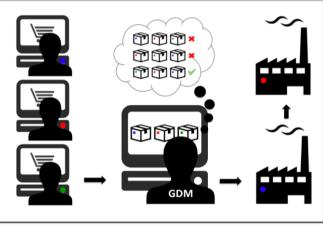


Figure 4. GDM in the PMBF Model

In the computational study, the PMBF was evaluated with 40 instances with a variable number of machines, tasks and two work centres. PMBF performed better than the FSBF model, with a mean deviation from best solution across all models of 0.23 *t.u*, and a standard deviation of 0.689 [2]. In these results no batching policies were considered, even when tasks would need to be transported between factories. In most real world multi-site production batching policies traditionally considered for the movement of in-production items across the production chain. The evaluation of the PMBF model performance under batching policies for the transportation of in-production items can demonstrate the practical application of the proposed model.

V. PMBF UNDER BATCHING POLICIES

The PMBF model should take into consideration the batch sizes to schedule operations. The $FF_C||C_{max}$ in multi-site production can be described as a MO (Multiple Objective) optimization problem, with two opposite objectives, the makespan minimization and the reduction of the delivery costs of in-production. The minimal makespan would reduce the idle time of the machines in the second factory with the reduction of the batch sizes while the minimal delivery costs would maximize the batch sizes. Since the makespan is not easily translated into a monetary cost, it is hard to reduce this MO problem into a weighted SO problem. One possible approach is to minimize the makespan within a defined batch size, which represents a delivery cost limit.

The PMBF result, under several batch sizes, will be compared to the results obtain from FSBF in [2], which does not take into account multi-site production. If the delivery costs of in-production items are taken into account, the multisite approach that previously appeared to have the best results appears to be much less attractive.

VI. COMPUTIONAL STUDY

The software developed in [2] was adapted to support the computational study and evaluate the sensitivity of the $FF_C||C_{max}$ multi-site production to different batch sizes. All three cases' performances were evaluated with 40 instances with a variable number of machines and two work centres, (No. of Machines X No. of Tasks: 2X10, 2X11, 2X12, 2X13, 2X14, 2X15, 2X16, 2X17, 2X18, 2X19, 3X10, ..., 3X19, 4X10, ..., 4X19, 5X10, ..., 5X19). All the instances data were randomly generated from the numbers {0; 1; 2; 3; 4; 5; 6; 7; 8; 9} and six batch sizes {1; 2; 4; 6; 8; 10}.

PMBF1 (batch size of 1) found the best solution in 35 (87.5%) instances, PMBF2 in 20 (50%), PMBF4 in 2 (5%), PMBF6 in 1 (2.5%), PMBF8 and PMFB10 did not found the best solution, as can be analysed in Fig. 5.

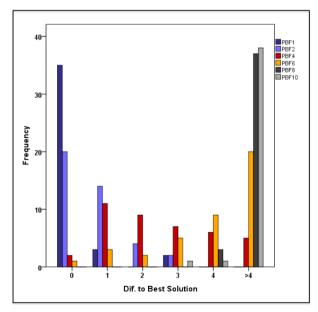


Figure 5. Bar Chart of the Solutions

Table I presents the parameters of the deviations of the PMBS model across all batch sizes. The boxplot from Fig. 6 permits to conclude that performance decreases with the increase of the batch size, in terms of minimization of makespan in the resolution of the analysed instances. This boxplot allows the analysis of location, dispersion, median and asymmetry of data of the six cases solutions when compared to the best solution across all cases.

TABLE L	PARAMETERS OF THE SOLUTIONS

	Mean	Median	Std. Deviation
PMBF1	0.23	0.0	0.698
PMBF2	0.70	0.5	0.853
PMBF4	2.55	2.0	1.648
PMBF6	4.85	4.50	2.601
PMBF8	9.40	9.0	4.144
PMBF10	11.30	10.0	5.585

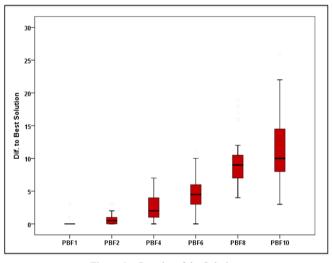


Figure 6. Boxplot of the Solutions

If compared with the results of the FSBF model obtained in [2], that can be seen in Fig. 7, it is possible to conclude that PMBF performed better up to batch sizes of 2 items. For the batch sizes of 4, 6, 8 and 10 the PMBF model resulted in higher makespan solutions than the FSBF model. These results cannot be assumed to be independent from number of parallel-machines in each of the work centres. More identical parallel-machines can better accommodate larger batch sizes as more items can be executed simultaneously and the conclusion times of the first operation would be similar across all tasks. In this case in production item would not need to wait as much for the rest of the items in the same batch to be executed as it would when there are fewer machines in each work centre.

To evaluate the significance of the obtained results we used ANOVA (Analyses of Variance), with the hypotheses:

H₀: $\mu_{PMBF0} = \mu_{PMBF2} = \mu_{PMBF4} = \mu_{PMBF6} = \mu_{PMBF8} = \mu_{PMBF10}$ H₁: At least one μ_{PMBF} is different

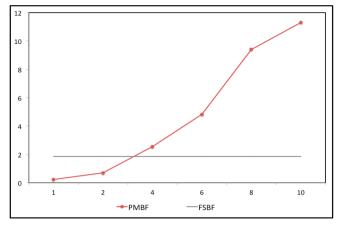


Figure 7. FSBF and PMBF with Batching

Table II shows the result of the ANOVA. It is not possible to assume equal means, as the null hypothesis H₀, which considers the non-existence of difference between all of the six cases performance, which was rejected with 95% of confidence level (*p*-value=0.000< α). Table III shows the results of the Scheffé's Homogeneous Subsets, that permits to demonstrate that the PMBF1, PMBF2 and PMBF4 cannot be assumed to be different (*p*-value=0.055), as is the case with PMBF4 and PMBF6 (*p*-value=0.066) and with PMBF8 and PMBF10 (*p*-value=0.201).

TABLE II. ANOVA

	Sum of Squares	df	Mean Squares	F	Sig.
B. Groups	4248.28	5	849.66	86.329	0.000
W. Groups	2303.05	234	9.84		
Total	6551.33	239			

TABLE III. SCHEFFÉ'S HOMOGENEOUS SUBSETS

	N	Subset of Alpha = 0.05			
		1	2	3	
PMBF1	40	0.23			
PMBF2	40	0.70			
PMBF4	40	2.55	2.55		
PMBF6	40		4.85		
PMBF8	40			9.40	
PMBF10	40			11.30	
Sig.		0.055	0.066	0.201	

In this case there are not statistical evidence about the existence of a difference in the PMBF model performance with batch sizes of 1, 2 and 4, 4 and 6, and 8 and 10. Since smaller batch sizes cost less, there are several batch sizes that represent an increase in the transfer's costs and have no impact in the model performance.

VII. CONCLUSIONS

The Distributed Flexible Flow Shop machine environment can characterize more complex and real production environments. In the context of the EMEs, network enterprises collaborate on distributed production chains that can often be described as Distributed Flexible Flow Shops. Production will flow over the network, with each enterprise responsible for one or more operations. Scheduling in distributed environments is much more complex, schedule boundaries are often hard to define, as networked enterprises have to collaborate and coordinate their operations. It was for this purpose that PMBF and FSBF models were proposed, based on distributed decision models. In the models the GDM and LDMs divide the schedule responsibilities, all based in well-known heuristics, such as the LTP, RLPT and the Johnson rule.

The computational study demonstrated how the PMFB model behaves with different batch sizes. Six batch sizes were used, (1, 2, 4, 6, 8 and 10) and it was showed that the solutions deteriorated as the batch sizes increased, from 0.23 t.u, with batch size of 1; up to 11.30 t.u, with batch size of 10. The PMBF solutions, as the batch sizes increased, were surmounted by the FSBF that does not include multi-site production. From the computational results it was possible to conclude with the ANOVA test, that the model performance with batch sizes of 1, 2 and 4 cannot be assumed to be different (p-value=0.055), as is the case with 4 and 6 (pvalue=0.066) and 8 and 10 (p-value=0.201). The PMBF behaviour cannot be assumed to be independent of number of parallel-machines in each factory. As the number of parallelmachines increase more items can be executed in simultaneously and the conclusion times of the first operation would be similar across all the tasks. In production items would not need to wait as much for the other items in the batch to be executed as it would when there were fewer machines.

In future this work will be extended with the development of batch size optimization approaches. The model should minimize the makespan, the delivery costs and proposed rush orders that do not wait for the rest of the batch to be release.

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