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A Dynamic Programming Operations Management Algorithim in a Tile Manufacturing Industry: Case Study of a Tile Company

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Abstract: *This research paper combined optimization algorithms, capacity planning, scheduling and discrete event simulation in the tile manufacturing plant, by determining the tooling, personnel and equipment resources that are required for optimal efficiency in the manufacturing process. A Dynamic Programming knapsack algorithm is used to optimally select jobs (in a 12-stage manufacturing process) such that they contribute to the production plan within a specified duration of time (28 days). This was done in such a way that each stage contributed to an overall optimal production plan for the tile manufacturing process with minimal costs. It is recommended that the designing of production processes should match volume-variety requirements, process design positioning and the incorporation of appropriate process technology. Furthermore job designs, recognising process variability, appropriately configuring process tasks, capacity and adopting a minimal cost task-precedence are also recommended.*

Keywords: *Capacity Planning, Scheduling, Knapsack Algorithm, Stage*

1. INTRODUCTION

Operations Management is an area of management concerned with overseeing, designing and redesigning business operations in the production of goods and/or services. It involves the responsibility of ensuring that business operations are effective in terms of using few resources so as to meet customer requirements. It is also concerned with managing the process that converts inputs (materials, labour and energy) into outputs (in the form of goods and/or services). An Algorithm is a step by step procedure which is expressed as a finite list of well-defined instructions. Algorithms are essential in industrial optimization and continue to be used in modern day industrial design. Tile industries are characterised by large scale production of a limited range of products. Over the last decade, consumer demand for tiles has become more sophisticated and the tile sector has been very competitive as a result of campaigns to ban the use of asbestos. The tile industry production system suffers from problems of finite products characteristics instability, information reliability along the supply-chain and high finite products inventory level. Sirtile Company is a tile manufacturing company in Zimbabwe that produces micro-concrete roofing tiles and less expensive, lighter, pigmented and textured roofing tiles. The company has been facing problems since its formation some ten years ago in its production planning, supply chain management and general operating. Waste due to waste of overproduction, waste of waiting, waste of transportation, waste of processing, waste of inventory, waste of motion, and waste of making defective items are common at this company. Despite the increasing demand for tiles, and the increasing competition as players increase in the sector, the majority of these Zimbabwean companies have failed to adequately fully exploit the high demand levels due to frequent breakdown of machinery, poor production management, and capacity planning. This paper aims to optimize the tile manufacturing production process by minimizing operational costs through capacity planning and maximizing production output by scheduling improvements. This will be done through identifying bottlenecks, determining if process tasks and capacity are configured appropriately, scheduling of machinery and personnel and deriving a cost-reduction model that can be adopted by production planners in the manufacturing process. Operations management has yielded a lot of improvements in global leading manufacturing industries. Improvements in lean production, total quality management, quality control aspects and other aspects of industrial optimization, have led to increased revenue in these innovative companies.

Process design is concerned with conceiving the overall state of a process and their detailed workings. The first of these tasks (conceiving the overall shape or nature of the process) can be approached by positioning the process in terms of its volume and variety characteristics. The second task (conceiving the detailed workings of the process) is more concerned with the detailed analysis of the objectives, capacity and variability of the process.

2. LITERATURE REVIEW

Various techniques, algorithms and methodologies have been adopted in the manufacturing sector. [1] in their research, "Using Simulation to Schedule Manufacturing Resources", discussed a real world application of simulation to schedule operator and machine resources in a floor tile manufacturing plant. The paper discussed attempts at using a spreadsheet, a simulator, and finally Pro-model in the manufacturing scheduling process. The key aspect in this paper is the idea of TAKT time. [2] developed a simulation tool for tile manufacturing companies. Their paper showed how simulation can be useful to support management decisions related to production scheduling and investment planning. Their aim was to demonstrate the importance of information systems in tile firms. The Factory Data Model (FDM) parameter was used to describe the activities in ceramic tile industries operating in different European countries. A process-based analysis of tile manufacturers is undertaken and the individual company performance is quantified by Key Performance Indicators (KPI's). The overall model composed of different processes, which were coded into Scilab environment and matched together to arrange a stochastic simulator. The simulation results were used to show how management decisions can significantly affect the KPI's. Queuing theory gives quantitative measures of the trade-off between cycle time and throughput rate of a manufacturing system [3. However, as pointed out by [4] when we attempt to apply queuing models to a real production system, even for a single machine, a number of issues are encountered. For example, real machines are subject to many kinds of interruptions, including breakdowns, set-ups and machine-operator interference. [5] described how to apply G/G/m approximations to evaluate the performance of manufacturing systems by defining service time (ST) using the notation of effective process time (EPT), which accounts for the theoretical process time, set-up, breakdown, and all other operational delays due to variability effects. Although these concepts are definitely useful, [6,7] pointed out that there is a systematic gap between effective process time and service time. In this paper we assume that queuing theory predicts system performance under the influence of randomness. The randomness mainly comes from natural variability of inter-arrival, service times and from interruptions. Interruptions can be either pre-emptive or non-pre-emptive, and are defined as any event which prevents machines from being productive. When there is no interruption and times are exponentially distributed, the M/M/c model suffices. If times are not exponentially distributed, the G/G/c model may be appropriate. Lean Production was introduced by [8]. The idea of lean thinking comprises of complex cocktail of ideas including continuous improvements, flattened organization structures, team work, elimination of waste, efficient use of resources and cooperative supply chain management [9]. As stated by [10] lean makes an organization more responsive to market trends, deliver products and services faster and produces products and services less expensively than non-lean organizations. According to [11], a planned implementation of lean techniques can also work well in non-manufacturing organizations such as banks, hospitals, restaurants, etc. [12] indicated that the selected companies that have adopted a wide variety of lean tools and techniques gained many performance improvements. Findings also identified the business challenges that drive the companies to practice lean as well as the areas where changes have been made. [13,14,15] presented the application of approximate dynamic programming (ADP) algorithm to the problem of job releasing and sequencing of a benchmark re-entrant manufacturing line (RML). The ADP approach is based on the SARSA algorithm with linear approximation structures that are turned through a gradient-descent approach. Results from these experiments showed a statistical match in performance between the optimal and the approximated policies obtained through ADP [16. Such results also suggest that the applicability of the ADP algorithm may be a promising approach for larger RML systems. In this paper, we also illustrate how a Dynamic Programming algorithm can be coupled with a simulation approach, and work in tandem to establish a functional work breakdown structure to schedule jobs in a manufacturing company.

3. Model Development

3.1 Research Design

In any manufacturing process, the system of collecting performance data is one of the important aspects of process analysis. In this study we have used a simplified data collection sheet that records process times at each stage of the manufacturing process. These include, time entity arrives in the system (stage), time service begins, time service ends and time entity leaves system stage. These times are then used to calculate cycle-times, throughput times and rates, utilization and other performance attributes.

3.1.1 Little's law

Little's law states that, under steady state conditions, the average number of items in a queuing system equals the average rate at which items arrive multiplied by the average time that an item spends in the system. Letting:

L = average number of items in the queuing system.

W = average waiting time in the system for an item.

λ = average number of items arriving per unit time.

The law is:

$$L = \lambda W \tag{1}$$

Little's law will be used to calculate the performance attributes in each stage of the manufacturing process.

3.2 Modelling Approach

The primary advantage of Dynamic Programming is its divide-and-conquer solution strategy. Using Dynamic Programming, a large, complex problem can be divided into a sequence of smaller interrelated problems. By solving the smaller problems sequentially, the optimal solution to the larger problem is found. In this paper we used the knapsack approach to formulate a Dynamic Programming model of the tile manufacturing line, where we let:

d_n = number of jobs in category n selected (decision variable at stage n).

x_n = number of days processing time remaining at beginning of stage n (state variable for stage n).

t_n = is a representation of a stage transformation function sequenced by each stage's number of days processing time remaining at the beginning of each stage and the number of jobs in category n selected.

r_n = is a representation of a stage transformation function, expressing the return at each stage.

($\alpha, \beta, ..., \mu$) are numerical constants (integers) which assign a value rating per each stage.

(A, B, ..., L) are the estimated completion times per job in each stage assigned by the supervisor.

Table 1. *Stages in the production process*

CATEGORY	Number of jobs to be processed	Estimated completion time per job (in hours)	Value rating
Sieving	a	A	α
Transport raw materials to mixing site	b	B	β
Mixing	c	C	γ
Moulding machine	d	D	δ
De-moulding	e	E	ε
Transport tiles to sandblast	f	F	λ
Preparing mixture for sand blasting	g	G	φ
Sand blasting	h	H	ϴ
Off laying	i	I	ф
Currying	j	J	π
Painting	k	K	Λ
Despatch and stores duties	l	L	μ

Thus with a 1 day production period, $x_{12} = 8$ represents the total number of hours available for processing jobs. We can then define the stage transformation functions so that:

Stage12: $x_{11} = t_{12}(x_{12}, d_{12}) = x_{12} - Ld_{12}$

Stage11: $x_{10} = t_{11}(x_{11}, d_{11}) = x_{11} - Kd_{11}$

Stage10: $x_9 = t_{10}(x_{10}, d_{10}) = x_{10} - Jd_{10}$

Stage9: $x_8 = t_9(x_9, d_9) = x_9 - Id_9$

Stage8: $x_7 = t_8(x_8, d_8) = x_8 - Hd_8$

Stage7: $x_6 = t_7(x_7, d_7) = x_7 - Gd_7$

Stage6: $x_5 = t_6(x_6, d_6) = x_6 - Fd_6$

Stage5: $x_4 = t_5(x_5, d_5) = x_5 - Ed_5$

Stage4: $x_3 = t_4(x_4, d_4) = x_4 - Dd_4$

Stage3: $x_2 = t_3(x_3, d_3) = x_3 - Cd_3$

Stage2: $x_1 = t_2(x_2, d_2) = x_2 - Bd_2$

Stage1: $x_0 = t_1(x_1, d_1) = x_1 - Ad_1$

The return at each stage is based on the value rating of the associated job category and the number of jobs selected from that category. The return functions are as follows:

Stage12: $r_{12}(x_{12}, d_{12}) = \mu d_{12}$

Stage11: $r_{11}(x_{11}, d_{11}) = \Lambda d_{11}$

Stage10: $r_{10}(x_{10}, d_{10}) = \pi d_{10}$

Stage9: $r_9(x_9, d_9) = \varphi d_9$

Stage8: $r_8(x_8, d_8) = \Theta d_8$

Stage7: $r_7(x_7, d_7) = \Phi d_7$

Stage6: $r_6(x_6, d_6) = \lambda d_6$

Stage5: $r_5(x_5, d_5) = \varepsilon d_5$

Stage4: $r_4(x_4, d_4) = \delta d_4$

Stage3: $r_3(x_3, d_3) = \gamma d_3$

Stage2: $r_2(x_2, d_2) = \beta d_2$

Stage1: $r_1(x_1, d_1) = \alpha d_1$

Where (α, β,..., μ) can take any values as assigned by the production planner.

We applied a backward solution procedure, i.e. we began by assuming that decisions have already been made for stages 12 - 2 and that the final decision remaining is how many jobs from category 1 to select at stage 1. Since regardless of whatever decisions have been made at various stages, if the decision at stage *n* is to be part of an optimal overall strategy, the decision made at stage *n* must necessarily be optimal for all remaining stages. We shall extract performance attributes of each stage in the manufacturing process so as to extract the job data for the manufacturing operation.

3.3 Modelling Assumptions

- We shall assume that the cycle times are constant throughout the project.
- Cycle times of various processes take constant and triangular distributions.
- Throughput rates of all processes stages have slight deviations which are negligible.
- The value-rating at each process stage is a variable parameter assigned by the production manager (for shift planning purposes) and is subject to change at various times of production planning.
- A day's shift is defined as 8 hours continuous shift with no stoppage or overtime.

4. DATA COLLECTION

We used the primary data of averages of cycle times taken from the Manufacturing process to calculate the input parameters for each stage.

4.1 Stage 1: Sieving

To prepare a mixture (mortar) for moulding 50 tiles, requires:

- 1 bag cement,
- 57 litres (0.057 cubic metres) of sand (1 unit),
- 24 litres water.

Therefore for 49 000 tiles for example, we require:

- (980 by 50 kg) cement,
- (980 by 57 litres) of sand,
- (980 by 24 litres) of water.

It takes an average of 10 minutes to sieve 57 litres of sand. If we define a job as sieving (48 by 57 litres) of sand, therefore (980 by 57 litres) is equivalent to 98 jobs. Hence for an estimated completion time of 1 day, we have 2 jobs.

4.2 Stage 2: Transporting Raw Materials to mixing site

It takes 4 minutes to move 1 sand wheelbarrow (57 litres) and 2 minutes to move 1 wheelbarrow of cement (with 2 bags) to the mixing site. Water is available at the mixing site from a pipe.

Therefore if we define a job at this stage as transporting 980 wheelbarrows, we have 2 jobs, with an estimated completion time of 2 days per job.

4.3 Stage 3: Mixing

It takes 5 minutes to mix 1 wheelbarrow of mortar mixture (for moulding 50 tiles). Therefore if we define a job as mixing 32 wheelbarrows, we have 10 jobs to be processed and the estimated completion time per job is 3 days.

4.4 Stage 4: Moulding Machines

Each moulding machine is operated by 2 personnel. It takes 1 minute to produce 1 tile, so we need approximately 1 hour to produce 50 tiles. If we define a job as producing 1600 tiles it therefore means we have 31 jobs with an estimated completion time of 4 days per job.

4.5 Stage 5: De-moulding

Each person de-moulds 1 tile in 1 minute. That is approximately 400 tiles in 8 hours. If we define 1 job as de-moulding 16333 tiles, we have 3 jobs with an estimated completion time of 5 days.

4.6 Stage 6: Transport Tiles to Sand Blasting

Each person can lay 1000 tiles per day. Therefore if we define a job as laying 7000 tiles, we have 7 jobs with an estimated completion time of 7 days per job.

4.7 Stage 7: Prepare MixturefFor Sand Blasting

It takes 5 minutes to prepare a mixture to blast 150 tiles in a mixing machine. If we define a job as preparing a mixture to blast 14400 tiles, we have approximately 4 jobs with an estimated completion time of 1 day per job.

4.8 Stage 8: Sand Blasting

Each person can blast 1000 tiles per day. If we define a job as blasting 7000 tiles, we have approximately 7 jobs with an estimated completion time of 8 days per job.

4.9 Stage 9: Off-laying

Each person can off-lay 1000 tiles per day. If we define a job as off-laying 7000 tiles, then we have approximately 7 jobs to be processed, with an estimated completion time of 7 days.

4.10 Stage 10: Currying

In this stage, tiles are stacked and are sprayed with water for 3 consecutive days. On average, 1 person can spray 49 000 tiles in 3 days. If we define a job as spraying 49 000 tiles, therefore we have 1 job to be processed with an estimated completion time of 3 days.

4.11 Stage 11: Painting and Stacking

Each person can paint 800 tiles per day. If we define a job as painting and stacking 8000 tiles, we therefore have approximately 6 jobs to be processed, with an estimated completion time of 10 days.

4.12 Stage 12: Stores and Dispatch Duties

We shall define a job as an average of conducting stores and dispatch duties for approximately 49 000 tiles, with an estimated completion time of 3 days. We shall assign a very high value rating because this stage will definitely have to be performed continuously during manufacturing.

5. MODEL APPLICATION

Appendix 1 shows the Dynamic Programming formulation of the job selection problem.

5.1 Calculating the Optimal Decisions for Each Stage

We shall use tables to help identify the optimal decisions at each of the 12 stages of the manufacturing process. The job data for the manufacturing operation is shown in Table 2 below.

Table 2. *Number of jobs and their estimated completion time*

CATEGORY	Number of jobs to be processed	Estimated completion time per job (in hours)	Value rating
Sieving	2	1	1
Transporting raw materials to mixing site	3	2	2
Mixing	10	3	3
Moulding machine	3	4	4
De-moulding	3	5	5
Transport tiles to sandblast	7	7	12
Preparing mixture for sand blasting	4	1	13
Sand blasting	7	8	14
Off laying	7	7	70
Currying	1	3	40
Painting	6	10	90
Despatch and stores duties	1	3	400

5.2 Data Analysis and Simulations

After we have completed the dynamic programming solution of our knapsack problem, in order to identify the overall optimal solution, we must now trace back through the tables, beginning at stage 12, the last stage considered in this paper. The optimal decision at stage 12 is $d_{12}^* = 1$, thus $x_{11} = x_{12} - 3d_{12}^* = 25$, which means we enter stage 11 with 25 days available of processing time to perform job tasks in the remaining stages. With $x_{11} = 25$, we see that the best decision at stage 11 is $d_{11}^* = 0$ (meaning that in this particular schedule we are planning in this 28 day period, instantaneously on this day, we can forgo to do stage 11 jobs that are waiting and choose other stage jobs). Thus we enter stage 10 with $x_{10} = 25$. The optimal decision at stage 10 with $x_{10} = 25$ is $d_{10}^* = 1$, thus $x_9 = x_{10} - 3d_{10}^* = 22$, and we enter Stage 9 with 22 days of processing. The optimal decision at Stage 9 with $x_9 = 22$ is $d_9^* = 1$, hence $x_8 = x_9 - 7d_9^* = 15$ and we enter Stage 8 with 15 days. The optimal decision at Stage 8 with 15 days is $d_8^* = 1$ hence $x_7 = x_8 - 8d_8^*$, thus we enter Stage 7 with 7 days of processing time. With 7 days of processing time at Stage 7, the optimal decision is $d_7^* = 4$ and $x_6 = x_7 - 1d_7^* = 5$, thus we enter stage 6 with 5 days of processing time. At Stage 6 the optimal decision with 5 days is $d_6^* = 0$, hence we enter Stage 5 with 5 days available for processing. At Stage 5, having 5 days for processing time, we have $d_5^* = 0$ or 1, hence we can either do one job at this stage or we do not do any job. If we choose not to do a job, we have $x_4^* = x_5 - 5d_5^* = 0$ we proceed to Stage 4 with 0 days of processing but if we choose not to do a job we have $x_4 = x_5 - 5d_5^* = 5$, we enter Stage 4 with 5 days of processing. This decision is subjective to the production planner, depending on the duration of time the job has been waiting to be processed. Suppose having chosen not to process a job at this stage, we enter Stage 4 with 5 days and the optimal decision at Stage 4 is $d_4^* = 1$ or 0 and $x_3 = x_4 - 4d_4^* = 5$ or 1. Again the production planner can choose whether to conduct a job or not depending on the duration of time the jobs have been waiting. Suppose we choose not to do a job, that is we proceed to Stage 3 with 5 days, meaning that the optimal duration at Stage 3 is $d_3^* = 1$, hence $x_2 = x_3 - 3d_3^* = 2$, and we proceed to Stage 2 with 2 days. With 2 days of processing at Stage 2, the optimal decision is $d_2^* = 0$ or 1, i.e. we can again choose not to do a job or do 1 job at this stage. If we do not do a job, we proceed to stage 1 with 2 days of processing, but if we choose 1 job we proceed with zero days of processing time to Stage 1, meaning that we cannot do any Stage 1 job since $x_1 = x_2 - 2d_2^* = 2$ or 0.

Suppose we do not do a job at Stage 2, we see that, at Stage 1 with 2 days, we have $d_1^* = 2$ so we can do two jobs. The optimal strategy for our manufacturing operation is as follows.

From Table 3 we can conclude that we should schedule 1 job from category 12, and 1 job from category 10, 1 job from category 9, 1 job from category 8, 1 job from category 7, 1 job from category 3, and 1 job from category 1, so as to archive an optimal production capacity for the next 28 days planning period.

Table 3. *Optimal strategy for the tile manufacturing problem*

Decision	Return
$d_1^* = 1$	2
$d_2^* = 0$	0
$d_3^* =1$	3
$d_4^* = 0$	0
$d_5^* = 0$	0
$d_6^* = 0$	0
$d_7^* = 4$	13
$d_8^* = 1$	14
$d_9^* = 1$	70
$d_{10}^* = 1$	40
$d_{11}^* = 0$	0
$d_{12}^* = 1$	400
Total Value	542

6. Sensitivity Analysis

It is of particular interest to note that the optimal decision at each stage is directly proportional to the value rating assigned to the particular category and the respective number of processing days required. To realise the effect of changes in the value rating we can analyse for a change in the value rating of Stage 12. Suppose it was assigned at a lower value of say 300, we have one job to be processed and we can recalculate the table for Stage 12 to be as in Table 4:

Table 4. *Change in the value rating*

d_{12}	$r_{12}(x_{12}, d_{12}) + f_{11}(x_{11})$		d_{12}^*	$f_{12}(x_{12})$	$X_{11} = x_{12} - 3d_{12}$
$X_{12} = 28$	0	1			
	344	300	0	344	28

The optimal decision at Stage 12 can be recalculated using this new figure to get the solution outlined in Table 5.

Table 5. *Optimal decision after change in the value rating*

Decision	Return
$d_1^* = 0$	0
$d_2^* = 0$	0
$d_3^* =0$	0
$d_4^* = 0$	0
$d_5^* = (0,1)$	(0, 5)
$d_6^* = 0$	0
$d_7^* = 4$	52
$d_8^* = 1$	14
$d_9^* = 1$	70
$d_{10}^* = 1$	40
$d_{11}^* = 0$	0
$d_{12}^* = 1$	0
Total Value	181

We can also test the sensitivity of our optimal solution to a small change in the total number of days available for processing. Suppose we want to schedule the jobs to be processed over a 14 day period only. We can solve this new problem simply by making recalculations at Stage 12. The new Stage 12 table will appear as in Table 6.

Table 6. *Change in the number of days*

d_{12}	$r_{12}(x_{12}, d_{12}) + f_{11}(x_{11})$		d_{12}^*	$f_{12}(x_{12})$	$X_{11} = x_{12} - 3d_{12}$
$X_{12} = 14$	0	1			
	165	400	1	400	11

Tracing through all the stages, we obtain the following optimal solution shown in Table 7.

Table 7. *Optimal decision after change in the number of days*

Decision	Return
$d_1^* = 0$	0
$d_2^* = 0$	0
$d_3^* = 0$	0
$d_4^* = 0$	0
$d_5^* = 0$	(0, 5)
$d_6^* = 0$	0
$d_7^* = 1$	13
$d_8^* = 0$	0
$d_9^* = 1$	70
$d_{10}^* = 1$	40
$d_{11}^* = 0$	0
$d_{12}^* = 1$	400
Total Value	523

7. Conclusion and Recommendations

7.1 Conclusion

From the calculations done it can be concluded that:

- The precedence relationship of jobs per each stage is creating bottlenecks which have in turn reduced the output of the whole manufacturing process.
- There is need for process balancing in stages 1 up to 6, as evidenced by successive queues.
- There is underutilization of resources, i.e. moulding machine personnel, off laying personnel, painting personnel, de-moulding personnel, sandblasting personnel and sieving personnel.
- There is significant starving of the moulding process caused by inadequate supply from the previous mixing process.
- As the capacity of tiles increases, there is significant blocking in the mixing stage and de-moulding stage.

7.2 Recommendations

The production planner must consider the overall shape and nature of the manufacturing process. The best way of doing this is by positioning it according to its volume and variety characteristics. The planner should also incorporate process analysis, which is a method of providing the detailed analysis of the process in order to refine its design. The Processes should match volume-variety requirements. [3] asserts that, the design of any manufacturing process should be governed by the volume and variety it is required to produce. This problem was also experienced in this research. Appropriateness of phases like process layout, process technology, job designs and process variability should be looked into in order to increase productivity and effectiveness of the production process.

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