Optimization of Cutting Parameters for Parallel Machine Scheduling with Constrained Power Demand Peak

Yi-Chi Wang*, Ming-Jun Wang, and Sung-Chi Lin

Industrial Engineering and Systems Management
Feng Chia University
Taichung, TAIWAN

ABSTRACT

Most of the past studies regarding machining optimization were based on machining science and economic considerations without the environmental dimension. Machining with higher cutting speed is usually desirable considering productivity, but requires high power load peak. In Taiwan, electricity price goes up sharply if the instantaneous power demand is over the contract capacity. Production scheduling problems have been widely studied for decades. However, majority of these studies consider jobs are known and processing times are certain. Besides, traditional sequencing and scheduling models deals with the economic objectives. There is still a severe lack of environmental considerations for production scheduling problems. In this study, we deal with a production scheduling problem for a manufacturing system with a bounded power demand peak. It is necessary to simultaneously determine proper cutting conditions for jobs and assign them to machines for processing without exceeding the electricity load limit at any point of time. A two-stage heuristic approach is proposed to solve the parallel machine scheduling problem with the goal of minimizing makespan. An illustrated instance with 3 machines and 20 jobs, each job in details with four possible cutting parameter settings for selection, is studied and employed to investigate the performance of the proposed heuristic.

1. INTRODUCTION

Climate change has become one of the greatest challenges facing nations, governments, organizations, enterprises, and peoples. It certainly will influence the way people work and live in future decades. The causes of the global environmental problems were commonly recognized from the depletion of natural resources and the pollution resulting from the life of technical products [1]. This led to increasing political pressure and stringer regulations being applied to both the manufacturers and the product end users. In 2000, energy related carbon dioxide equivalent (CO2e) emissions represented about 65 % of the global greenhouse gas emissions, while about 24 % and 14 % of CO2e emissions were attributed to power generation and industrial activity respectively [2]. One of the recent survey conducted by U.S. Energy Information Administration in 2013 pointed that the industrial sector consumes about one-half of the world total delivered energy. It again indicated energy management should be a priority in industrial sectors. Manufacturing is the key for industrial sector. Furthermore, a large and growing number of manufacturers are realizing substantial financial and environmental benefits from sustainable business practices. Therefore, sustainable manufacturing, which was defined as making products through economically-sound processes that minimize negative environmental impacts considering conservation of energy and natural resources, has become an important issue and even drawn increasing attention of people from both industry and academia.

Reduction of energy usage that can directly cut down carbon emission has being increasingly recognized as one of the important trends in sustainable manufacturing. This same trend has applied in machining technologies [1, 3, 4]. A significant amount of research has been undertaken on the environmental issues of a machine tool system, while most of these studies focus the analysis of chipping processes, dealing with the influences of material removal and cutting fluids, in parallel to the electricity consumption impact [5]. However, a machining task is performed by a machine tool that relies on electricity as its main power source. Santos et al. [5] pointed that machine tools have been identified as one of the main energy-using products to be analysed in an Eco-design perspective, targeting the reduction of their environmental impact. From micro perspective, the major power demand of a modern machine tool system come from spindle rotation and servo-driven axis movement [4]. Optimum cutting parameters then becomes imperative when minimizing the energy consumed by the machine during machining. In literature, optimization of machining conditions

* Corresponding author: Tel.: (+886) 424517250-3637; Fax: (+886) 424510240; E-mail: wangyc@fcu.edu.tw

has been studied for decades, but most of the studies were based on machining science and economic considerations without the environmental dimension. Mativenga and Rajemi [6] concluded that minimum energy criterion can be used to significantly reduce the cost, energy and carbon footprint of machined products.

From macro-level perspective, when a set of jobs are to be processed by a manufacturing system consists of several modern CNC machine tools, traditional sequencing and scheduling models deals with the economic issues like costs, makespan, job tardiness, throughput, etc.. There is still a severe lack of energy saving considerations for production scheduling problems. In this paper we consider a problem of scheduling a set of jobs on parallel machines while a set of machining conditions for each job are provided for selection. The system objective is to minimize makespan under a limited power demand during machining. The remainder of this paper is organized as follows. Section 2 provides a review for parallel machine scheduling problems with flexible resources. In Section 3 we introduce the considered problem in details. In Section 4 a two-stage heuristic for solving the illustrated problem is proposed. In Section 5 we report the computation result of each stage of the proposed heuristic. Section 6 concludes with a summary and suggestions for further research.

2. Literature Review

Parallel machine scheduling problems have been widely studied for decades. Most studies for classical parallel machine scheduling problems assumed that processing times are fixed for jobs. However, processing times in reality may be controllable based on the amount of resources allocated. The resources could be flexible for use like manpower, financial support, fuel, energy, etc. [7]. Early research about controllable processing times in single machine and two machine scheduling problems was surveyed by Nowicki and Zdralka [8]. Shabtay and Steiner [7] provided a more comprehensive survey of results for scheduling problems with controllable processing time. They reviewed the past studies from the perspectives of both single and multi- machine problems. The other great survey was presented by Edis et al. [9]. They classified the related studies in a framework with five categories: machine environment, additional resources, objective functions, complexity results, and solution methods.

Daniels and Mazzola, [10] pointed resource flexibility in a flow shop environment can have a significant impact on the quality of a schedule when job processing times depend on the amount and mix of resources dedicated to an operation. Daniels et al. [11] further demonstrated that the improvements in operational performance can be achieved through the deployment of a flexible resource for an environment of parallel manufacturing cells. They provided mathematical formulations for both two versions (static and dynamic) of the parallel-machine flexible-resource scheduling problems (PMFRS). In static PMFRS problems, resource allocation decisions remain unchanged throughout the scheduling horizon, while for the dynamic version of PMFRS problems, resource can be reassigned to machines any time when a job is completed. If the assignment of jobs to machines is not specified, the problem is named an unspecified PMFRS (UPMFRS) problem, where an additional job-machine assignment sub-problem must be solved. Daniels et al. [12] proposed and compared two heuristics for testing over 800 static UPMFRS. They concluded that the tabu search- based heuristic outperformed the other one on cost and quality effective of optimal solution searching. Edis and Oguz [13] extended the formulation of dynamic PMRFS problems of Daniels et al. [11] and presented mathematical models of the static and dynamic UPMFRS problems. The static PMFRS problem can be solved in polynomial time, while the dynamic PMFRS, static and dynamic UPMFRS problem are all NP-hard [11, 12].

3. Problem Statement

The UPMFRS problem considered in this study may be stated as follows: There exist 20 independent single-operation jobs available for processing at time t =0. For each job, the manufacturer engineers and cutting tool providers suggest four options of cutting conditions for selection. The detailed job descriptions for all the 20 jobs are presented in Appendix 1. All the options and their corresponding machining time and power demand are listed in Table 1. Each job can be processed on any one of 3 identical CNC turning machines. Each machine can process at most one job at a time, and job preemption is not allowed in this case. The objective is to minimize makespan for all these 20 jobs.

The only constraint is that at any time the electrical power demand peak cannot exceed 25 KW for job production with the 3-machine cell. The upper bound of the power demand can be viewed as the additional flexible resource except the machines. It is continuous and renewable. When the cutting condition for a turning operation is determined, the material removal rate (MRR) defined as the volume of material removed per unit time can be calculated. Given the specific cutting energy of the workpiece material, the power demand with the cutting parameter setting can be obtained by multiplying the specific cutting energy and MRR. In the resulting problem, three decisions must be jointly made to solve the scheduling problem: determining machining conditions for jobs, specifying jobs-machines assignment, and determining start machining times for jobs.

Table 1. Machining Times and Power Demands for Machining Conditions Suggested.

Job	Cutting Condition 1		Cutting Condition 2		Cutting Condition 3		Cutting Condition 4	
	Machining time(min)	Power Demand(KW)	Machining time(min)	Power Demand(KW)	Machining time(min)	Power Demand(KW)	Machining time(min)	Power Demand(KW)
1	3.27273	13.823	4.31655	10.4804	5.14286	8.79646	7.2	6.28319
2	6.94377	10.7076	8.60606	8.63938	9.7931	7.59218	11.0506	6.72824
3	5.02994	13.9906	6.5625	10.7233	8.15534	8.62891	10.9091	6.45074
4	4.11111	12.2499	4.85246	10.3784	5.63809	8.93226	6.72727	7.48608
5	11.5	13.406	12.9577	11.8978	16.7273	9.21664	23.5897	6.53543
6	6.27692	13.5853	8.16	10.4502	9.6	8.88266	13.1613	6.47912
7	18.2941	13.0855	22.8257	10.4876	27.3407	8.75573	37.1343	6.44652
8	0.985185	13.9418	1.37824	9.96577	1.81199	7.58018	2.34155	5.86587
9	5.65517	11.423	6.92958	9.32219	8.2	7.87791	9.84	6.56492
10	0.72956	11.7993	0.849817	10.1296	1.16583	7.38384	1.40606	6.12228
11	1.13996	14.7833	1.46946	11.4684	1.77577	9.49016	2.08053	8.10005
12	9.43284	14.2473	12.3922	10.8449	16.1019	8.34634	21.9826	6.11356
13	17.1236	11.5957	21.4648	9.2505	26.2759	7.55675	30.48	6.51444
14	3.93043	12.5572	4.56566	10.8101	5.54601	8.89926	6.79699	7.26136
15	7.21905	12.6768	9.94098	9.20577	12.3755	7.3948	15.16	6.03657
16	1.3964	12.8872	1.83976	9.78152	2.06667	8.70759	2.7193	6.61777
17	0.824	10.6524	0.922732	9.51255	1.10013	7.97861	1.29356	6.78555
18	2.225	12.9533	2.94215	9.79594	3.99103	7.22147	4.57584	6.29855
19	10.8833	14.0035	16.1235	9.45239	19.2059	7.93534	22.9123	6.65168
20	1.58844	13.0877	1.89517	10.9695	2.5211	8.24602	3.15862	6.58169

4. A Proposed two-stage Heuristic for the Problem

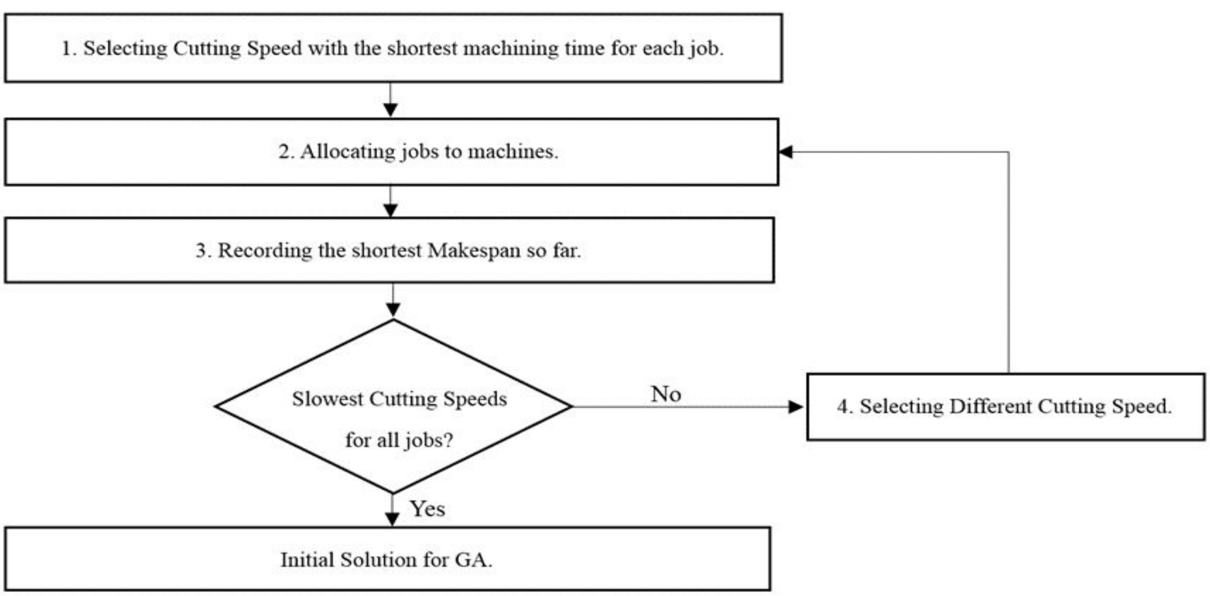

Figure 1. Flow Chart for Stage One of the Proposed Heuristic.

Although three decisions mentioned in previous section must be determined jointly to solve this dynamic UPMFRS problem, it may be advantageous to partition the entire problem into three sub-problems and solve sub-problems one or two at a time. In this section, we explain the two-stage heuristic in which an initial solution is obtained at the first stage and then it is improved by using a genetic algorithm-based (GA) method at the second stage.

4.1. Stage One of the Heuristic

At the first stage, we develop an approach with four steps running iteratively. A flow chart for the first stage of the proposed heuristic is shown in Figure 1.

Step 1 - Selecting cutting speed with the shortest machining time for each job. Since the objective is to minimize the system makespan. Intuitively, performing the operations with their highest cutting speeds given should be preferable. At this point, the constraint of power demand peak is not considered.

Step 2 - Scheduling jobs to machines. A longest machining time (LMT) priority rule is employed to assign the jobs to the three identical turning machines by sequencing jobs to the first available machine one by one in decreasing order of job machining time. With cutting speed determined and the machine specified for a job, setting the start time for processing the job must take the upper bound of power demand into consideration. For example, if two of the three machines are operating and the system power remaining is not enough for the third machine to process the job. The start time of the job then will be scheduled right after enough power is released from the other two machines. With such logic to schedule the jobs, a production schedule for the 20 jobs will be constructed.

Step 3 - Comparing the makespan of the new production schedule with the previous best schedule. If the new schedule is better, then replacing the previous best schedule with the current one obtained.

Step 4 - Selecting different cutting speed. At the beginning, we favor the highest cutting speed in order to make shorter makespan. However, machining high cutting speed requires more power which may cause some idle time since simultaneously performing the jobs requiring high power demands may result in the power demand peak exceed the upper bound. For two parameter settings in increasing order of job machining time, a ratio defined as the gap of power demands divided by the difference of machining times can be used to select the job and try the slower cutting speed.

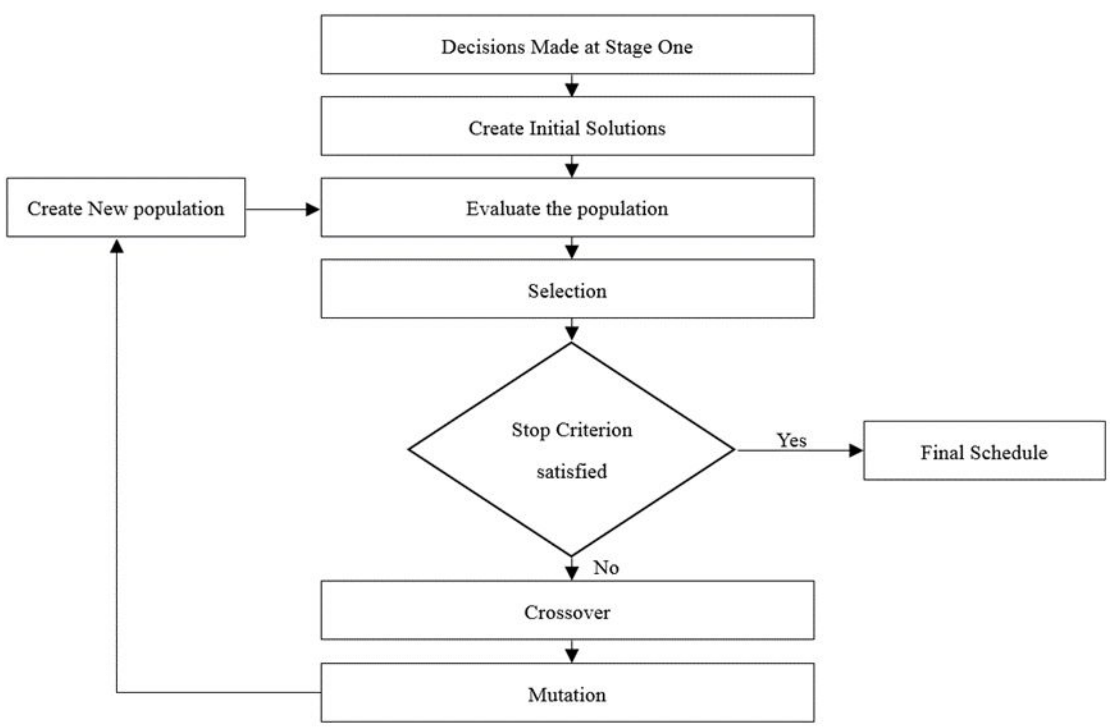

Figure 2. Flow Chart for Stage Two of the Proposed Heuristic.

After stage one, the sequence of assigning jobs to machines and which machine a job is assigned to are presented in Table 2.

Table 2. Job-Machine Assignments Determined at Stage One.

Assigning Sequence	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Job #	7	13	5	12	19	15	2	6	9	3	1	14	4	18	20	16	8	11	10	17
Machine	1	2	3	2	1	3	2	3	1	1	2	3	3	2	1	1	2	3	2	1

4.2. Stage Two of the Heuristic

Some portion of the solution obtained at the first stage is used as the initial solution for the GA at this stage. We have the two decisions inherited from stage one: the machining conditions and sequence of assigning jobs to machines. We leave the decision (assignment of jobs to machines) to be made at the second stage. A GA is then employed to determine which machine a job is assigned to. Genetic algorithms (GAs), usually viewed as search procedures based on the mechanics of artificial selection and genetic recombination operators, have been successfully applied to solving a wide range of difficult problems. The GA in this study consists of the following elements: initial solutions, evaluation, selection, crossover, and mutation. Figure 2 shows the logic of the proposed GA.

Chromosomes and Initial Population - A solution (schedule) can be represented by a chromosome in a set of strings of machine number (the 3rd row of Table 2). The population size is set to 15. With the job sequence unchanged, we generate 14 solutions by randomly assigning jobs to one of the three machines and add the best one found at the first stage.

Evaluation - For each generation, all the solutions generated are measured by their makespans. The chromosomes representing the solutions are further ranked in ascending order according to their makespans.

Selection - The best 5 solutions are selected out of 15 to be potential parents for next generation.

Crossover - From the top 5 solutions of the generation, two of them are randomly selected to be the parents being mated for breeding their offspring through crossover operator. The crossover mechanism is shown in Figure 3. A single crossover point is randomly picked. The strings on left side of the crossover point in parent 1(P1) are copied to the matching positions of the offspring 1(O1), and the rest of the positions in P1 are copied to the matching positions of offspring 2(O2). Each time two selected parents are mated to generate two children. We randomly select one of the two children for survival. The procedure is repeated until 15 offspring are all generated.

Mutation –For each offspring chromosome, two genes are randomly selected. The probability of swapping the two selected genes is set to 20%. Figure 4 shows how the mutation mechanism operates.

Job #	7	13	5	12	19	15	2	6	9	3	1	14	4	18	20	16	8	11	10	17
Machine(P1)	1	2	3	2	1	3	2	3	1	1	2	3	3	2	1	1	2	3	2	1
Machine(P2)	2	3	1	1	2	3	2	1	3	3	1	2	1	2	3	1	3	2	1	2

Job #	7	13	5	12	19	15	2	6	9	3	1	14	4	18	20	16	8	11	10	17
Machine(O1)	1	2	3	2	1	3	2	3	1	3	1	2	1	2	3	1	3	2	1	2
Machine(O2)	2	3	1	1	2	3	2	1	3	1	2	3	3	2	1	1	2	3	2	1

Figure 3. An Example for Crossover Operator of the Proposed GA.

Job #	7	13	5	12	19	15	2	6	9	3	1	14	4	18	20	16	8	11	10	17
Machine(O1)	1	2	3	2	1	3	2	3	1	3	1	2	1	2	3	1	3	2	1	2

Swap

Figure 4. An Example for Mutation Operator of the Proposed GA.

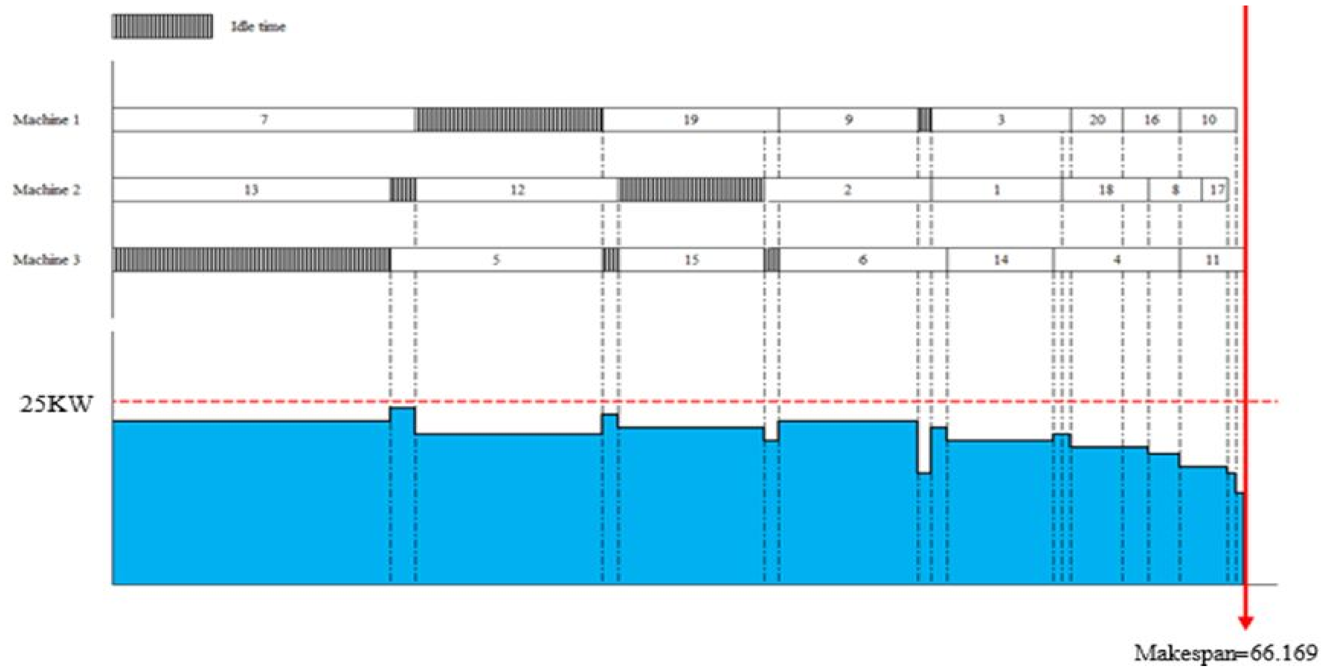

Figure 5. The Production Schedule and the Profile of Power Demand obtained at Stage One.

5. RESULTS AND ANALYSIS

In this section, performance of the proposed heuristic is evaluated through stage by stage. At the first stage, the complete schedule found is shown in Figure 5. The makespan is 66.169 minutes. The bottom graph presents profile of the power demand during machining. It can be observed that the power demand is reached about 80% of 25 KW for the prior period of the makespan, and it drop to 60%~70% of 25 KW in later period.

At the second stage, the proposed GA improves the schedule obtained at stage one. Figure 6 shows the complete production schedule and profile of the power demand. The makespan is 55.001 minutes. The GA makes about 17% improvement in makespan. It should be noted that 11.168 minutes of saving is all the idle time since the same machining conditions has been determined and applied for both cases. For the profile of power demand, the power demand is balanced perfectly and it reaches about 95~98% of 25 KW.

6. CONCLUSIONS

The current needs to sustainable production in manufacturing industry require proper selection of machining conditions with economic and environmental considerations. Higher cutting speeds are usually desirable considering the performance measure of productivity, but may cause high power load peak. In Taiwan, electricity price goes up sharply if the instantaneous power demand is over the contract capacity, which is predetermined and reported to Taiwan Power Company. In this study, we deal with a scheduling problem for a manufacturing system with a bounded power demand peak. The problem turns out to the dynamic parallel-machine flexible-resource scheduling problem with unspecified job-machine assignment (UPMFRS). A two-stage heuristic is proposed for solving this UPMFRS. The machining parameters for the jobs are determined at the first stage, and the jobs are optimally scheduled at the second stage of the proposed heuristic. Future research effort needs to evaluate the proposed heuristic by testing more large-sized problems.

ACKNOWLEDGEMENTS

This study was supported by the National Science Council of Taiwan under Contract No. NSC 100-2221-E-035-076-MY3.

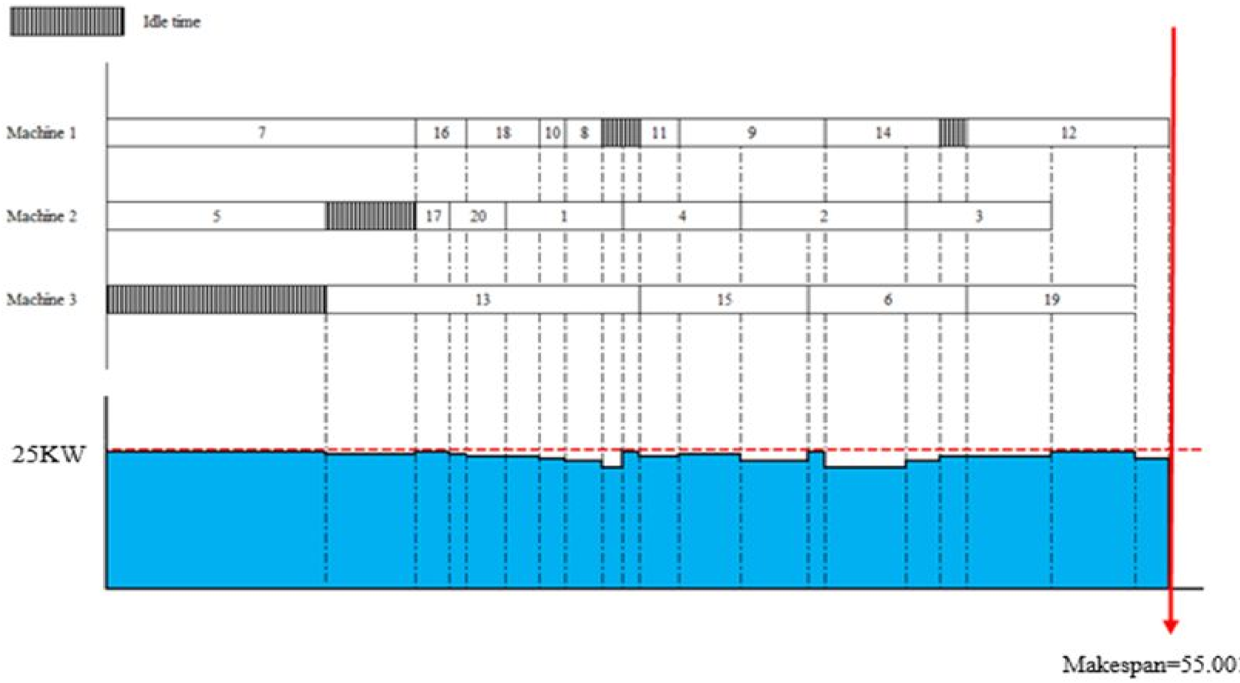

Figure 6. The Production Schedule and the Profile of Power Demand found at Stage Two.

REFERENCES

[1] F. Pusavec, P. Krajnik, and J. Kopac: *"Transitioning to Sustainable Production – Part O: Application on Machining Technologies", Journal of Cleaner Production, Vol.18, No.2, pp.174–184, 2010.*

[2] M.F. Rajemi, P.T. Mativenga, and A. Aramcharoen: *"Sustainable Machining: Selection of Optimum Turning Conditions based on Minimum Energy Considerations", Journal of Cleaner Production, Vol.18, No.10–11, pp.1059–1065, 2010.*

[3] O.I. Avram and P. Xirouchakis: *"Evaluating the use phase energy requirements of a machine tool system", Journal of Cleaner Production, Vol.19, No.6-7, pp.699–711, 2011.*

[4] M. Mori, M. Fujishima, Y. Inamasu, and Y. Oda: *"A study on energy efficiency improvement for machine tools", CIRP Annals – Manufacturing Technology, Vol.60, No.1, pp.145–148, 2011.*

[5] J.P. Santos, M. Oliveira, F.G. Almeida, J.P. Pereira, and A. Reis: *"Improving the environmental performance of machine-tools: influence of technology and throughput on the electrical energy consumption of a press-brake", Vol.19, No.4, pp.356–364, 2011.*

[6] P.T. Mativenga and M.G. Rajemi: *"Calculation of Optimum Cutting Parameters Based on Minimum Energy Footprint", CIRP Annuals – Manufacturing Technology, Vol.60, No.1, pp.149–152, 2011.*

[7] D. Shabtay and G. Steiner: *"A Survey of Scheduling with Controllable Processing Times", Discrete Applied Mathematics, Vol.155, No.3, pp.1643–1666. 2007.*

[8] E. Nowicki and S. Zdralka: *"A Survey of Results for Sequencing Problems with Controllable Processing Times", Discrete Applied Mathematics, Vol.26, No.2–3, pp.271–2887, 1990.*

[9] E.B. Edis, C. Oguz, and I. Ozkarahan: *"Parallel Machine Scheduling with Additional Resources: Notation, Classification, Models and Solution Methods", European Journal of Operational Research, Vol.230, No.3, pp.449–463, 2013.*

[10] R.L. Daniels and J.B. Mazzola: *"Flow Shop Scheduling with Resource Flexibility", Operations Research, Vol.42, No.3, pp.504–552., 1994.*

[11] R.L. Daniels, B.J. Hoopes, and J.B. Mazzola: *"Scheduling Parallel Manufacturing Cells with Resource Flexibility", Management Science, Vol.42, No.9, pp.1260–1276, 1996.*

[12] R.L. Daniels, S.Y. Hua, and S. Webster: *"Heuristics for Parallel-machine Flexible-resource Scheduling Problems with Unspecified Job Assignment", Computers & Operations Research, Vol.26, No.2, pp.143–155, 1999.*

[13] E.B. Edis and C. Oguz: *"Parallel Machine Scheduling with Flexible Resources", Computers & Industrial Engineering, Vol. 63, No.2 , pp.433–447, 2012.*

APPENDIX 1: DETAILED DESCRIPTIONS FOR JOBS

Job	Material	Specific Energy (Nm/mm^3)	Original Diameter(mm)	Length(mm)	Final Diameter(mm)	Depth of cut(mm)	Feed(mm/rev)	Cutting Conditions Spindle (RPM)			
								1	2	3	4
1	Carbon Steel	1.6	80	450	50	15	0.25	550	417	350	250
2			250	710	240	5		409	330	257	200
3			400	210	380	10		200	150	143	110
4	Alloy Steels	4.4	211	148	197	7		144	105	88	79
5			253	230	512	11.5		80	71	55	39
6			336	204	325.2	5.4		100	85	77	50
7			259	622	246.1	6.45		300	270	255	225
8	Cast Irons	1.1	76.3	332.5	57.5	9.4		1350	1190	1000	850
9			359	123	308.2	25.4		77	60	50	40
10			176.5	58	147.3	14.6		318	273	199	165
11			213.4	157.6	196	8.7		553	429	355	303
12	Stainless Steel	2.8	142.2	632	121.8	10.2		355	273	245	192
13			269.3	381	242.9	13.2		89	71	58	50
14			156.8	226	137.8	9.5		230	204	163	133
15			337.5	151.6	313.1	12.2		155	142	100	73
16	Magnesium alloys	1.1	99.3	155	58.7	20.3		444	394	300	228
17			108	206	94.3	6.85		1000	893	749	664
18			65	445	30.4	17.3		800	749	691	599
19	Bronze	2.2	273.8	326.5	244.2	14.8		150	123	90	77
20	Aluminum	0.7	346.9	68.7	299.3	23.8		173	145	109	127