Int j simul model 14 (2015) 1, 98-109
ISSN 1726-4529 Original scientific paper

MULTI OBJECTIVE OPTIMIZATION FOR SUSTAINABLE MANUFACTURING, APPLICATION IN TURNING

Hassine, H.[*,**]; Barkallah, M.[*]; Bellacicco, A.[**]; Louati, J.[*]; Riviere, A.[**] & Haddar, M.[*]
[*] Laboratory of Mechanical Modeling and Manufacturing, National Engineering School of Sfax, University of Sfax, Tunisia
[**] Laboratory of engineering of the Mechanical Structures and Materials, Height Institute of Mechanic of Paris, Saint Ouen, France
E-Mail: hassinehichem@yahoo.fr

Abstract
As manufacturing converts raw materials into products, environmental wastes and emissions are simultaneously generated from the consumption of materials and energy during the manufacturing processes. Then, sustainable manufacturing is defined as the creation of manufactured products using processes that minimize negative environmental impacts, conserve energy and natural resources and that are safe on employees, communities and consumers. Such an approach requires a compromise between ecological and economic aspects to meet the pillars of sustainable development.

This paper presents the implementation of particle swarm tool in order to solve multi-objective optimization for sustainable manufacturing. Hence, this study might serve as part of a global approach to model sustainable manufacturing. The main objective of this approach is to develop operations that allow production with respect of ecological, economic and technological constraints. We developed a case study on the cutting conditions during turning at the end of our study.
(Received in March 2014, accepted in August 2014. This paper was with the authors 3 months for 5 revisions.)

Key Words: Sustainable Manufacturing, Multi Objective Optimization, Particle Swarm Optimization, Turning

1. INTRODUCTION

In recent years, energy consumption and environmental impact of manufacturing processes have gained great concern in response to the global trends towards sustainable manufacturing. The reasons for this concern include regulation requirements, product stewardship, enhanced public image, potential to expand customer base and potential competitive advantages.

Intensive energy consumption in industry has drawn increasing attention due to its adverse environmental impact and the exhaustion of natural resources. According to the International Energy Agency, the energy consumed by manufacturing industries accounts for 30 % of the total world energy, and 36 % of the global CO_2 emission.

Reducing the energy impact can help companies accomplish green production. Some authors have developed a model of the sustainable manufacturing base energy. So far, energy has been indirectly considered in machining optimization through including power as a constraint in the optimization problem. Then, in 1981, De Fillippi et al. integrated energy as an objective in their study [1]. Later, in the mid-90s, Munoz and Sheng [2] proposed an environmentally-conscious multi-objective model which considered energy consumption as the most important component. It also presented a global approach to carry out an optimization procedure from an ecological perspective. Haapala et al. [3] studied a series of manufacturing processes like sand casting, bending, welding and laser cutting using steel in the production process. Their objective was to estimate materials, energy consumption and waste correlated using a spreadsheet.

Gutowski et al. [4] studied the energy requirements for various manufacturing processes. They concluded that the specific energy requirement varies with respect to unit processes, which is in opposition to the way the energy process is treated in most LCA studies.

Dietmair and Verl [5] presented a model for energy consumption by machines, which were then shown for milling. Diaz et al. [6] studied the impact of different rates of material removal on the specific energy requirements for a milling machine. The study found that the machining time is a major cause of higher energy consumption. Nava [7] studied a method to minimize energy consumption and carbon footprint of the metal forming process considering the energy of the mechanical work, energy conversion to CO_2, and providing an optimization approach to minimize the resulting CO_2 emissions. Rajemi et al. [8] developed a methodology to model the energy consumption for machining processes. Their model was illustrated by the turning process which identifies the effect of the process parameters on energy consumption.

Kara and Ibbotson [9] developed a comparative study of some production scenarios based on energy consumption and its environmental impact. Fang et al. [10] studied the application of linear programming to optimize the load peak power and energy consumption of manufacturing systems.

In the United States, a global commission of researchers has developed a method of analysis of the manufacturing processes using LCA, Kellens et al. [11, 12]. The method quantifies the energy consumption for the manufacturing processes using data found in literature or experimentation.

Thus, the optimization in manufacturing is a crucial step in the commercial product life. Economic benefits (time, cost…) were the main objectives of this step taken into account technical constraints. Then, in recent activities, in order to integrate sustainability notion, ecology was introduced as a constraint. To this end, some authors have tried to use some algorithms to achieve these objectives: There are genetic algorithms and the particle swarms.

The multi-objective optimization is a tool commonly used in decision based on the weight and respect some constraints.

Belaidi [13], used the NSGAII algorithm to optimize functions of both of the target cost and time on milling. It applied the same algorithm used for constraint optimization in turning. Chibane et al. [14] coupled functions of time and production cost with the quality of the surface obtained using genetic algorithms. Jin et al. [15] have developed the first multi-objective optimization approach for the integration of environmental stress. Their study aims to use a fuzzy model to obtain optimum cutting parameters minimizing the cost, time and environmental issues. Hoffenson et al. [16] have tried to link the economic, ecological and human pillars using the Monte Carlo method. They applied their model to the manufacture of mobile phones.

We notice that research in the sustainable manufacturing field tried to develop some important pillars such as energy and materials but optimization is not well developed because of the number of settings used, constraints in manufacturing and performances of numerical algorithms for optimization.

Then, from the developed approach, we can conclude that a sustainable manufacturing suffers from a general approach that takes into account ecological, economic and technological issues. Since the sustainable manufacturing concept is very complicated in terms of an efficient and effective use of energy using the available resources and the process environment. This complexity, therefore, affects the design process of the conceptual modelling to integrate all of the important aspects. The design of a systematic approach is critically required. Therefore, we tried to develop a framework to model a low ecological impact manufacturing relying on a multi objective optimization. To improve the sustainable manufacturing field, we need to consider some ecological issues as an objective and not a constraint.

This paper aimed to present the modelling of a multi objective optimization based on the integration of the environmental aspects using the Particle Swarm Optimization (PSO) tool.

The remaining of this paper was organized as follows. Section 2 introduced implementation of the multi objective optimization in sustainable manufacturing modelling. Section 3 was devoted to detail the optimization algorithm used. Our case study was thoroughly discussed in section 4. Our results were displayed and discussed in the fifth section before drawing our conclusions in the final section.

2. MULTI OBJECTIVE OPTIMIZATION MODELLING FOR SUSTAINABLE MANUFACTURING

The procedure of using resources that enable companies to meet human needs while the environment is preserved for the present and the future is called sustainable development. The term sustainable development was first used in 1987 in the Brundtland Report. On the other hand, the environmental impact from enterprise and manufacturing processes has been considered as a timely topic in recent decades. From this point of view, it leads to the need of environmental responsibility associated to products and processes.

In an attempt to achieve sustainable manufacturing we presented an approach based on the optimization of resources consumption and the reduction of environmental impact. Fig. 1 introduces the different steps of this algorithm.

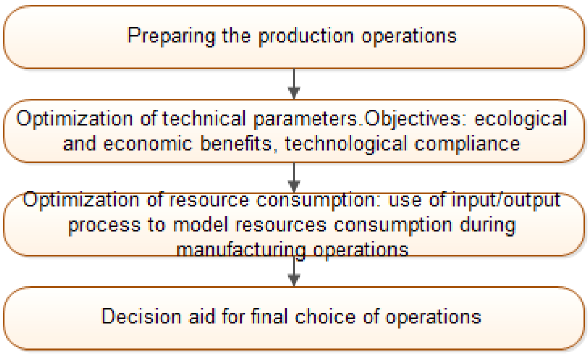

Figure 1: Modelling sustainable manufacturing approach.

To achieve sustainable manufacturing, our approach is based on modelling the energy, the material and the process. For the development of such a framework and conceptual modelling, various scientific tools were incorporated such as IPO model, optimization algorithms …

Such modelling enables decision makers to evaluate the energy consumption from processes, resource allocation optimization and undesired wastes associated with the ecological impacts.

The main objective of the framework is to provide the appropriate solution in manufacturing level in order to achieve energy efficiency, resource utilization and waste minimization.

We tried in this paper to present one of the important steps in this approach that is optimization of the technical parameters that further minimize the ecological impact, production time and cost under some technical constraints. Minimizing the ecological impact is defined as an objective related to the economic benefit (time and cost).

Principle: The overall goal of optimizing in production is the minimization of the production time and cost of a given product taking into account the quality of the product such as roughness. “Optimization” for sustainable manufacturing is a compromise between economic gain and harmful emissions control from the production. The objective functions summarize the transaction time, the operation cost and emissions. An optimization problem is expressed as an objective function for one or more variables to be maximized or minimized in a number of specified constraints.

The following equation expresses the general mathematical form of an optimization problem.

Minimize $f(x)$ as: $x \in R^n$ under functions constraints:

$$\begin{cases} g_j(x) \leq 0 \text{ for } j = 1, \ldots, m \\ h_i(x) = 0 \text{ for } i = 1, \ldots\ldots, l \\ x_{p\,\min} \leq x_p \leq x_{p\,\max} \text{ for } p = 1, \ldots, n \end{cases}$$

In this equation $f(x)$ is the mathematical expression of the objective function (or function of economic optimization criterion) with the vector components for $x \in R^n$ $(x_1, x_2, ..., x_n)$ are the variables (or unknown) of the problem. Then $g_j(x)$ and $h_i(x)$ represent functions' constraints that define the acceptable range of variables for the optimization process. Such stresses, which can be equal or unequal types, allow the limitations on the variable fields in the mark (or) optimal solution(s).

Modelling the environmental objective function: Manufacturing is one of the stages in the life cycle of a production that directly consumes resources, generates environmental pollution emissions and causes occupational health and safety problems. Then, modelling the resources consumption in the mechanical manufacturing operation depends on the following balances: material balance, energy balance and emissions balance.

The energy component is an important key toward sustainable manufacturing: the majority of our current energy is generated by fossil fuels which account for two thirds of the world's greenhouse gas emission.

In this paper, we presented the environmental function as an energetic function that summarizes the energy consumption during the operation. The total energy is a combination of basic, idle and tip powers over time. Each power level is a reflection of the use of various components or sub-operations of the machining process, such us loading and unloading, indexing tooling, axis movement, punching, drilling or bending.

3. MULTI OBJECTIVE OPTIMIZATION

Multi objective optimization is a problem with many objectives to be satisfied. These objectives are usually in conflict with each other. Constrained optimization, however, is an optimization problem with one or more constraints to be fulfilled.

For the optimization problems, we tried to look for heuristic solutions that approach the required result. Among these heuristics, some algorithms have a suitable generic principle and thus are suitable to many optimization problems. They are called meta-heuristics. The most common is the stochastic descent: starting with an initial solution, compared to all its neighbours every time maintaining the best result. An important number of meta-heuristic algorithms such as genetic algorithms (GA), evolutionary algorithm (EA), simulated annealing (SA), artificial bee colony algorithm (ABC), particle swarm optimization (PSO) were developed to solve this multi objective problem.

These methods are summarized by Zitzler et al. [17]. Cus and Balic [18], and Saravanan et al. [19], among others, proposed approaches based on GA to solve multi-objective optimization problems for machining processes while Liu and Wang used a modified genetic algorithm for the optimization of the cutting parameters in milling [20].

Wang et al. [21] presented the genetic simulated annealing (GSA) and parallel genetic simulated annealing (PGSA) based on the genetic algorithm and simulated annealing to find optimal machining parameters in milling operations. Baskar et al. [22] compared the performance of four non-conventional methods: Ant Colony Algorithm, GA, PSO and Tabu Search. These methods were applied to determine the optimal process parameters in order to optimize time, cost and profit rates. The results showed that PSO has a better performance than the other algorithms. It was reported that 44 % and 54 % of improvement in profit rate was achieved compared to handbook recommendation and optimal result by using feasible direction method. However, the comparison of the obtained results from GA and PSO showed that the optimal results for these algorithms do not differ by more than 4 %.

According to this study and other framework in the optimization field, PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. It has been applied in multiple fields such as human tremor analysis for biomedical engineering, electric power and voltage management and machine scheduling.

This tool was developed by Russell Eberhart, an electrical engineer, and James Kennedy, a social psychologist [23]. This method is based on the collaboration between individuals: each particle moves, and, at each iteration, the closest to the optimum communicates the best position to the others so that they change their trajectory. The idea is that a group of individuals having a limited intelligence can have a complex global organization. From the development of this algorithm, a lot of research relied heavily on the PSO, but the most effective, so far, has been the extension to the combinatorial optimization framework. Indeed, in 2000, Maurice Clerc, a researcher at France Telecom set up the DPSO (Discrete Particle Swarm Optimization), by replacing the points with schedules and continuous functions by evaluation functions.

3.1 The algorithm principle

The particle swarm optimization derives from the stochastic descent family of algorithms. It draws heavily on gregarious migratory birds relationships. These birds have to travel long distances and therefore need to optimize their journey in terms of energy expenditure and thus the need for the V formation [24, 25].

The swarm in PSO started with a number of random solutions. Each particle has a position and a velocity, representing the potential solution to the problems and the search direction of the particle in the search space, respectively. The particle adjusts its velocity and position according to the best experiences called *pbest* found by itself and *gbest* found by all its neighbours. Fig. 2 shows the different steps of the PSO process.

Applying the PSO method consists in applying the steps presented in Fig. 2. These steps depend on a typical particle swarm movement toward the optimum solution.

3.2 Movement of the particle during simulation

The principle of the PSO algorithm is based on a population called swarm of possible solutions. These particles are placed randomly in the search space of the objective function.

At each iteration, the particles move taking into account their best position (selfish movement) but also the best position of its neighbours (penuries displacement).

Fig. 3 presents a geometrical view of the movement of the particle in PSO. In fact, the new speed is calculated using the following formula:

$$V_{\mathrm{k+1}} = c_1 v_k + c_2(B_p - P_p) + c_3(B_v - P_p) \tag{1}$$

with:

V_{k+1} and v_k are the velocities of the particles iterations k and $k+1$, B_p is the best position of the particle, B_v is the best position of its neighbours at iteration k, P_p is the position of the particle at iteration k, c_1, c_2, c_3 are fixed coefficients, c_2 is randomly generated at each iteration, and in general $c_2 = c_3$.

We can then determine the next position of the particle with the speed that we just calculated: $P_{k+1} = P_k + V_{k+1}$

We generate P_0 and V_0 at the beginning of our algorithm.

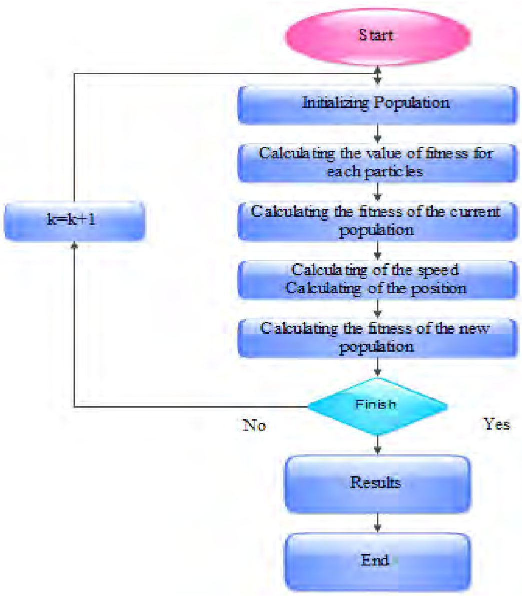

Figure 2: PSO Algorithm.

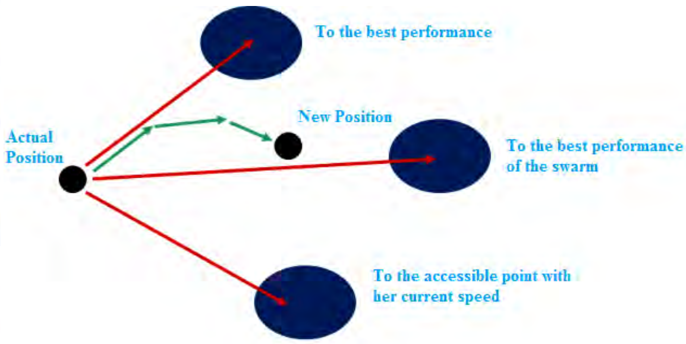

Figure 3: Movement of the particle at each iteration.

3.3 Particle swarm optimization for sustainable manufacturing problem

In this paper we used the PSO for the optimization of problems with boundary constraints. This means that the search space $S = [lb_1\ ub_1] \times [lb_2\ ub_2] \times \ldots \times [lb_n\ ub_n]$ consists of n real-valued parameters $(x_1, ..., x_n)$ where each parameter x_i, $1 \le i \le n$, is bounded with respect to some interval $[lb_i\ \ ub_i]$.

The PSO is a population based stochastic search algorithm for global optimization. Each individual denoted as particle moves through the n dimensional search space S of an optimization problem with an objective function f. This framework presents a minimization of three objective functions to search two technical parameters.

Each particle has a position, a velocity and a fitness value and remembers the best position it has visited so far as its private guide. Furthermore, each particle is able to communicate with a subset of all particles, denoted as its neighbourhood.

In each iteration we calculate the new velocity and position of the particle using eq. (1). This algorithm tried to repeat these steps to achieve a stopping criterion that determines the optimal solution of this problem.

3.4 Weighted aggregation approach

According to this approach, all the objectives are summed to a weighted combination. These weights can be either fixed or dynamically adapted during the optimization.

Aggregation represents an important problem in multi objectives optimization. Many approaches could be named as illustrations such as: conventional weighted aggregation (CWA), Bang-Bang weighted aggregation (BWA), Dynamic weighted aggregation (DWA) …

During the run, we used in this to aggregate the objectives with equal weight fixed in the beginning of the simulation algorithm.

4. CASE STUDY: ROUGHING OPERATION IN TURNING

In this framework we aim to optimize cutting parameters in roughing operation: cutting speed v_c, feed rate f to ensure the minimization of the three objective functions production time (f_1), production cost (f_2) and energy consumption (f_3). To this end, some production constraints have to be taken into consideration.

Then the mathematical formulation of the problem is: min F ($F = f_1(v_c, f) + f_2(v_c, f) + f_3(v_c, f)$) with respect to the technical constraints $g_i = (g_1, g_2, g_3, g_4, g_5)$. The optimal parameters searched depend of the following boundaries: $0.254 \leq f \leq 0.762$ mm/rev. and $80 \leq v_c \leq 200$ m/min.

First objective: Production time: The total time required for the production of a piece is equal to the sum of the time required to machine the part, fixed time (study setting), tool change time, technological cutting time.

The general expression of machining time is expressed by the following equation:

$$f_1 = t_l + t_m + t_r\left(\frac{t_m}{T}\right) \tag{2}$$

The lifetime of the cutting tool depends on the cutting conditions. According to Taylor, we have:

$$T = k^{-1/n} v_c^{1/n} f^{-p/n} a^{-q/n} \tag{3}$$

The values of the exponents n, p, q of the generalized Taylor law depend primarily on the material of the tool. The coefficient k is a function of the material being machined, the tool used and the wear criterion adopted.

In roughing, the technological cutting time is given by the following expression:

$$t_m = \frac{\pi D L}{1000 v_c f} \tag{4}$$

Second objective: Production cost: The cost of a part is equal to the sum of all the costs of manufacturing, machine cost, a stop cutting auxiliary launch cost and room cost. The general expression for the total cost of production is given by the following expression:

$$f_2 = p_0 t_l + p_a + p_0 t_m + p_l\left(\frac{t_m}{T}\right) \tag{5}$$

Third objective: Energy consumption: The environmental function depends essentially on the energy, material and methods used to shape the product. Modelling the energy consumed at the location is defined according to the following expression:

$$E = E_1 + E_2 + E_3 + E_4 \tag{6}$$

Gutowski et al. [4] defined the energy material removal as follows:

$$E_2 = (p_0 + k_1 \dot{v}) t_m \tag{7}$$

The energy consumed during turning is defined as follows:

$$f_3 = P_0 t_l + (P_0 + k_1 \dot{v}) t_m + P_0 t_r\left(\frac{t_m}{T}\right) + Y_E\left(\frac{t_m}{T}\right) \tag{8}$$

Production constraints: Apart from the objective function, some constraints need to be satisfied. While some are related to the machine tool capabilities, others are derived from product requirements.

Limitation of cutting power: The values of the cutting conditions should be chosen so that the cutting power P_c is at most equal to the maximum power available on the spindle machine tool P_u. Therefore: $P_c \leq P_u$. In the case of turning, the cutting power is given by the following expression:

$$g_1 = P_c = \frac{k_f a f^{0.7} v_c}{60} \leq P_u \tag{9}$$

Limitation the allowable torque on the spindle: The torque applied to the spindle of the machine must not exceed a limit value $c_{\max}$ which is independent of the cutting speed.

$$g_2 = \frac{k_f a f^{0.7} D}{2} \leq C_{max} \tag{10}$$

Limitation with the tool: During a cutting operation, it is necessary to split the chip, because the long chips are dangerous to the operator and difficult to remove. For fragmented chips, we use some chip breakers which are dimensioned according to the cutting conditions used.

To ensure the efficiency of this tool we respect the following constraint:

$$g_3 : 0.05 \leq \frac{f}{a}(\sin k_r)^2 \leq 0.3 \tag{11}$$

Limitation associated with the work piece: In turning, it is generally accepted that the boom must not exceed a maximum value Z_{max} that considers the following relation:

$$g_4 = \frac{k_f a f^{0.7} L^3}{2.4 E D^4} \leq Z_{max} \tag{12}$$

Restrictions related to the surface are given by the equation expressing the total theoretical roughness compared to the actual maximum roughness that must not be exceeded.

$$g_5 = R_{tth} = \frac{1000 f^2}{8 r_\varepsilon} \leq R_{t\,max} \tag{14}$$

Parameters for simulation: We summarized the parameters used for simulation in Table I.

Table I: Data used in simulation.

Tool parameters	Symbol	value	unit
Fixed time	t_l	1.5	min
Time tool change	t_r	0.5	min
Machine cost	p_0	0.1	Euro/min
Cost of a stop cutting	p_l	0.5	Euro/edge
Auxiliary cost launch series	p_a	0.1	Euro
Length	L	203	mm
Diameter	D	152	mm
Power consumed by the machines	P_0	3495	W
Specific energy required for operation	k_1	4.3	Ws/mm^3
Taylor's exponents	n, p, q, k	-0.25, -0.29, -0.35, 193.3	/
Energy per cutting edge	Y_E	1325000	J
Depth of cut	a	1.5	mm
Roughness	$R_{t\,max}$	2	µm
Maximum power	P_u	5000	W

5. RESULTS AND DISCUSSION

We present the results of modelling with a depth of cut equal to 1.5 mm and using steel as the material for the work piece. Then, the size of the used swarm is 80 particles and the PSO parameters were fixed as $c_1 = 0.9$ and $c_2 = 0.5$. Then a certain weight has to be given to the objectives depending on the requirements in order to incorporate the importance of each of the objectives ($W_1 = W_2 = W_3 = 1/3$).

Analysis of cutting parameters: The main objective of our framework is to determine optimal cutting parameters that minimize time, cost and energy consumption during roughing operation. Fig. 3 presents the evolution of these parameters during simulation.

The analysis of the evolution of both cutting parameters shows that the optimum value is reached from iteration 400. For a depth of cut about 1.5 mm, the optimum cutting speed is 156.33 m/min and the optimal feed rate about 0.762 mm/rev.

Optimal cutting parameters found are conforming to empirical value used for this type of operation. It provides the desired surface state and respects tool life desired.

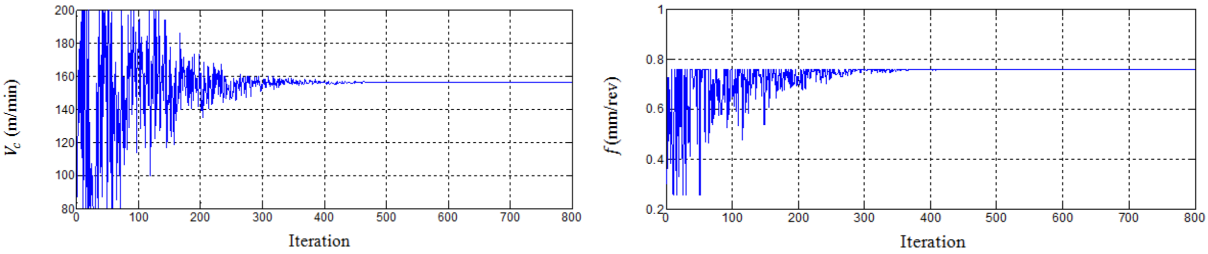

Figure 4: Variation of optimal parameters during simulation.

These optimal cutting parameters guarantee the minimum cost, time and energy consumption. They also depend on the different constraints and machining conditions. Therefore, we notice that these results of cutting parameters can be further developed with the integration of other constraints.

Analysis of objective functions: Energy is one of the most important pillars toward a sustainable manufacturing. We aimed in this model to combine the economic and the energetic objectives. Figs. 5, 6, and 7 show the evolution of these objectives during simulation of the roughing operation. The minimum cutting time in the cutting conditions is 1.29 min. This result is reached from iteration 400. At the same iteration we obtained the minimum production cost (2.54 euro) and minimum energy consumption (9.5775 10^6 J).

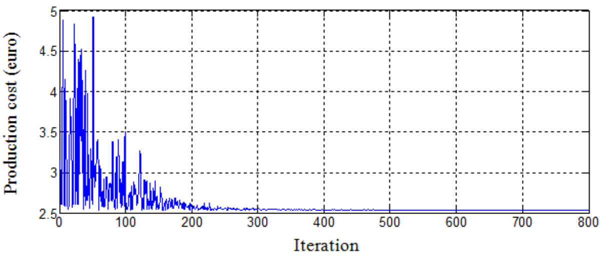

Figure 5: Production cost.

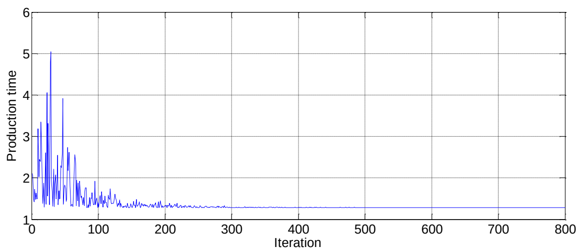

Figure 6: Production time.

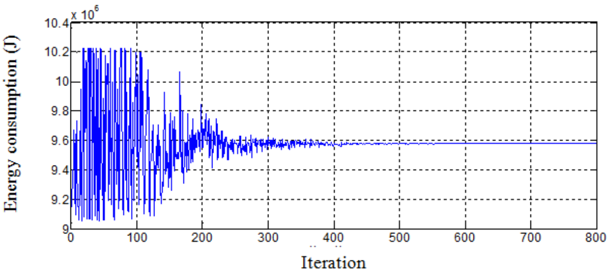

Figure 7: Energy consumption.

The same Figs. 5, 6, and 7 also show the optimal value of objective functions that coupled the economic and energetic pillars. We can conclude that these results presented the optimal cutting parameters and objectives that summarize the notion of sustainable machining or green production.

Influence of depth of cut: In practice, the depth of cut represents an important cutting parameter that influences the quality of result obtained in optimization. In Table II we present the results of modelling for different values of depth of cut.

Table II: Results of optimization for different depths of cut.

a	0.5	1.5	2.5	4	5
f_1	1.0024	1.2878	1.4934	1.7845	1.9890
f_2	2.2524	2.5378	2.7434	3.0345	3.2390
f_3	$9.2187 \cdot 10^6$	$9.5775 \cdot 10^6$	$9.9601 \cdot 10^6$	$1.0619 \cdot 10^7$	$1.1126 \cdot 10^7$
v_c	191.65	156.33	145.39	138.65	136.72
f	0.762	0.762	0.762	0.762	0.762

Depending on depth of cut, the variation of the time and the cost of production are important. But energy consumption has varied slightly. We can conclude here that respecting the environmental aspect has caused an important increase in the production cost.

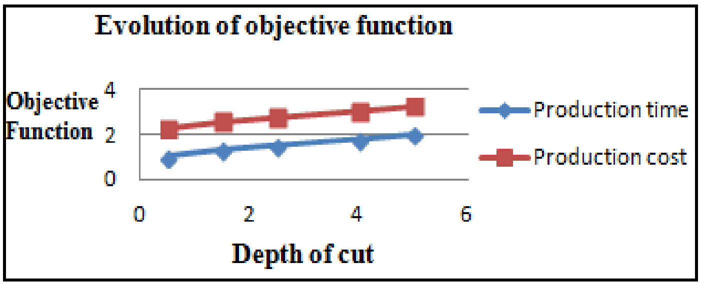

Figure 8: Effect of depth of cut on the evolution of objective function.

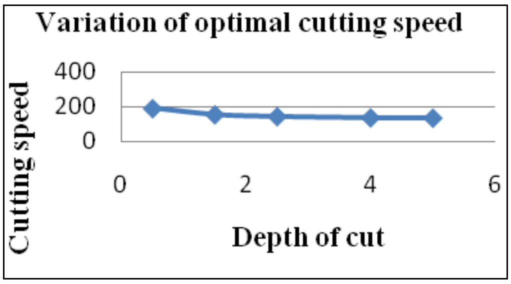

Figure 9: Effect of the depth of cut on the evolution of optimal cutting speed.

We notice that cutting speed decreases with the increase of the depth of cut. But cost, time and energy increase with the increase of this cutting parameter (Fig. 8). The production cost in this case study includes only the operation cost but a sustainable machining depends also on the material used. Therefore, the material used, the lubricant and the auxiliary material can be added to the objective function.

Fig. 9 shows that the cutting speed decreases when the depth of cut increases to achieve the minimum cost, time and energy consumption. According to these results, we can determine the optimal cutting speed for some values of depth of cut.

This approach for optimization of cutting parameters can be developed for different steps in the product life cycle to achieve 'Low carbon manufacturing'. This expression has been coined to reflect a comprehensive effort to reduce CO_2 emissions generated from the directly consumed energy by manufacturing activities. Applying the particle swarm optimization for sustainable manufacturing allows us to define the idea of coupling the economic and the ecological objectives. But, to apply this type of approach in machining operation, we need an accurate study of the different process parameters.

6. CONCLUSION

Achieving increased energy efficiency has become increasingly vital with the ever-growing energy demand threatened by future probable shortages. Using energy more efficiently is often a cost effective way of cutting on carbon dioxide emissions which also improves productivity and contributes to the security of our future energy supply.

Energy efficiency can be defined as using less energy while maintaining the same level of service. It can be achieved either by decreasing total energy use or increasing the production rate per unit of energy consumed.

We presented in this paper the optimization for the cutting conditions in turning using a multi objective optimization coupling ecological and economic objectives. The particle swarm optimization shows the effectiveness of the model in terms of accuracy of the results and response time. For the aggregation problem, we treated the optimization with an equal fixed weight. But, an approach of aggregation in optimization for sustainable manufacturing can be developed. These weights can be developed using a multi criteria decision aid method taken into account: user, environmental regulation and economic strategies of the society.

In turning, we conclude that we can act on the cutting speed to reduce the cost, time and energy consumption at production. Feed rate is slightly influential in the results.

Thus, to achieve respect for the ecology, we notice that economic cost is going to be necessarily. This is noticeable in terms of the variation of the objective function based on the depth of cut high.

In this paper, the quality of resulting surface was modelled as a constraint but in future work, we can define roughness as an objective to be achieved by our model functions.

The developed method can be extended to other machining processes and we can develop other objective functions that consider other basic components of sustainable manufacturing. Then to achieve sustainable machining with low CO_2 emissions, we have to integrate the other pillars of a sustainable development: material and technology.

REFERENCES

[1] De Filippi, A.; Ippolito, R.; Micheletti, G. F. (1981). NC machine tools as electric energy users, *CIRP Annals – Manufacturing Technology*, Vol. 30, No. 1, 323-326, doi:10.1016/S0007-8506(07)60950-0

[2] Munoz, A. A.; Sheng, P. (1995). An analytical approach for determining the environmental impact of machining process, *Journal of Materials Processing Technology*, Vol. 53, No 3-4, 736-758, doi:10.1016/0924-0136(94)01764-R

[3] Haapala, K. R.; Khadke, K. N.; Sutherland, J. W. (2004). Predicting manufacturing waste and energy for sustainable product development via WE-Fab software, *Proceedings of the Global Conference on Sustainable Product Development and Life Cycle Engineering*, Vol. 8, 243-250

[4] Gutowski, T.; Dahmus, J.; Thiriez, A. (2006). Electrical energy requirements for manufacturing processes, *Proceedings of the 13th CIRP International Conference on Life Cycle Engineering*, 623-627

[5] Dietmair, A.; Verl, A. (2008). Energy consumption modeling and optimization for production machines, *IEEE International Conference on Sustainable Energy Technologies*, 574-579

[6] Diaz, N.; Redelsheimer, E.; Dornfeld, D. (2011). Energy consumption characterization and reduction strategies for milling machine tool use, Hesselbach, J.; Herrmann, C. (eds.), *Globalized Solutions for Sustainability in Manufacturing*, Springer, Berlin, 263-267

[7] Nava, P. (2009). *Minimizing carbon emissions in metal forming*, M.S. Thesis, Department of Mechanical and Materials Engineering, Queen's University, Kingston, Ontario

[8] Rajemi, M. F.; Mativenga, P. T.; Aramcharoen, A. (2010). Sustainable machining: selection of optimum turning conditions based on minimum energy considerations, *Journal of Cleaner Production*, Vol. 18, No. 10-11, 1059-65, doi:10.1016/j.jclepro.2010.01.025

[9] Kara, S.; Ibbotson, S. (2011). Embodied energy of manufacturing supply chains, *CIRP Journal of Manufacturing Science and Technology*, Vol. 4, No. 3, 317-323, doi:10.1016/j.cirpj.2011.03.006

[10] Fang, K.; Uhan, N.; Zhao, F.; Sutherland, J. W. (2011). A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction, *Journal of Manufacturing Systems*, Vol. 30, No. 4, 234-240, doi:10.1016/j.jmsy.2011.08.004

[11] Kellens, K.; Dewulf, W.; Overcash, M.; Hauschild, M. Z.; Duflou, J. R. (2012a). Methodology for systematic analysis and improvement of manufacturing unit process life-cycle inventory (UPLCI) – CO_2PE! initiative (cooperative effort on process emissions in manufacturing). Part 1: Methodology description, *International Journal of Life Cycle Assessment*, Vol. 17, No. 1, 69-78, doi:10.1007/s11367-011-0340-4

[12] Kellens, K.; Dewulf, W.; Overcash, M.; Hauschild, M. Z.; Duflou, J. R. (2012b), Methodology for systematic analysis and improvement of manufacturing unit process life cycle inventory (UPLCI) CO_2PE! initiative (cooperative effort on process emissions in manufacturing). Part 2:

Case studies, *International Journal of Life Cycle Assessment*, Vol. 17, No. 2, 242-251, doi:10.1007/s11367-011-0352-0

[13] Belaidi, I. (2007). A model based on the NSGA-II for multi-objective optimization of Roughing parameters (in French), *Colloquium AIP-PRIMECA 2007*, La Plagne

[14] Chibane, H.; Serra, R.; Leroy, R. (2011). Implementation of a multi-objective optimization shooting a 100C6 steel: compromise between surface quality and productivity (in French), *20th French Congress of Mechanics*, Besancon, 6 pages

[15] Jin, K.; Li, H.; Zhang, H. C.; Nage, S. (2012). Multi-Objective Tooling Optimization for Sustainable Manufacturing, *International Journal of Engineering Research and Applications (IJERA)*, Vol. 2, No. 1, 853-862

[16] Hoffenson, S.; Dagman, A.; Soderberg, R. (2013). A Multi-objective Tolerance Optimization Approach for Economic, Ecological, and Social Sustainability, *20th CIRP International Conference on Life Cycle Engineering*, Singapore, 6 pages

[17] Zitzler, E.; Laumanns, M.; Bleuler, S. (2004). A tutorial on evolutionary multiobjective optimization, Gandibleux, X. et al. (eds.), *Metaheuristics for Multiobjective Optimisation*, Springer, Berlin, 3-37, doi:10.1007/978-3-642-17144-4_1

[18] Cus, F.; Balic, J. (2003). Optimization of cutting process by GA approach, *Robotics and Computer-Integrated Manufacturing*, Vol. 19, No. 1-2, 113-121, doi:10.1016/S0736-5845(02)00068-6

[19] Saravanan, R.; Asokan, P.; Sachidanandam, M. (2002). A multi-objective genetic algorithm (GA) approach for optimization of surface grinding operations, *International Journal of Machine Tools and Manufacture*, Vol. 42, No. 12, 1327-1334, doi:10.1016/S0890-6955(02)00074-3

[20] Liu, Y.-M.; Wang, C.-J. (1999). A modified genetic algorithm based optimization of milling parameters, *International Journal of Advanced Manufacturing Technology*, Vol. 15, No. 11, 796-799, doi:10.1007/s001700050134

[21] Wang, Z. G.; Rahman, M.; Wong, Y. S.; Sun, J. (2005). Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing, *International Journal of Machine Tools and Manufacture*, Vol. 45, No. 15, 1726-1734, doi:10.1016/j.ijmachtools.2005.03.009

[22] Baskar, N.; Asokan, P.; Prabhaharan, G.; Saravanan, R. (2005). Optimization of machining parameters for milling operations using non-conventional methods, *International Journal of Advanced Manufacturing Technology*, Vol. 25, No. 11-12, 1078-1088, doi:10.1007/s00170-003-1939-9

[23] Kennedy, J.; Eberhart, R. (1995). Particle swarm optimization, *Proceedings of the IEEE International Conference on Neural Networks*, Vol. 4, 1942-1948, doi:10.1109/ICNN.1995.488968

[24] Nor Azlina, A. A.; Mohamad, Y. A.; Ammar, W. M.; Kamarulzaman, A. A. (2011). Particle swarm optimization for constrained and multi objective problems: A brief review, *International Conference on Management and Artificial Intelligence IPEDR*, Vol. 6, 146-150

[25] Voratas, K. (2012). Comparison of three evolutionary algorithms: GA, PSO, and DE, *Industrial Engineering and Management Systems*, Vol. 11, No. 3, 215-223, doi:10.7232/iems.2012.11.3.215