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Simulation analysis for sustainable manufacturing: A green roadmap

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Abstract

Rapid industrial growth is adversely attributed with drastic environmental degradation, forcing the manufacturing industry to seek quantifiable measures for sustainability of its products and processes. Other than satisfying scientific acumen and commercial intention; environmental impact research is a major thrust area of manufacturing. In this research, we aim to develop an eco-friendly and efficient manufacturing process (milling) that minimizes resource utilization. Minimizing energy and pollution were used to quantify sustainability, whereas noise intensity and aerosol concentration quantified conduciveness of the work environment. Laboratory experiments were conducted to obtain data using which simulation modeling and analysis was conducted. This analysis helped in identifying significant factors that affect the eco-efficiency of this unit manufacturing process. The results provide an opening to develop a green roadmap for sustainable (Green) manufacturing.

Keywords
Green Manufacturing, Work environment, Simulation.

1. Introduction
From last few years, manufacturing units are under immense pressure to look after the social as well as environmental factors, above the economical benefits of their proceedings and products. It has resulted into change in the mindset of manufacturers and now they are focusing to stimulate those manufacturing processes and manufactured goods that diminish the environmental impacts at the same time maintaining socio-economic benefits. This scenario has put forward a challenge in front of the manufacturing industry worldwide to withstand the cut-throat competition in the market by adopting and implementing sustainable manufacturing methods and equipment. Now, enterprises have started finding the sustainability measurement way outs; although, some efficient measurement techniques are there for estimating the effects of manufacturing on the environment and society.

1.1 Motivation

The encouragement for this paper has been aroused from the urgency to recognize the energy consumption during metalworking and machining-based production systems. Different levels of analysis, ranging from minute tool-chip interface to the gigantic enterprise, and every level of analysis consisting of comparable temporal scale of decisions; ranging from few nano-seconds at tool-chip level to several weeks at organization level has brought into light in the paper by Vijayaraghavan, and Dornfeld (2010). Figure 1, which is reproduced from the same citation, reveals the amount of variation in the analysis, and temporal scales as well as the types of decisions that are made at each level.

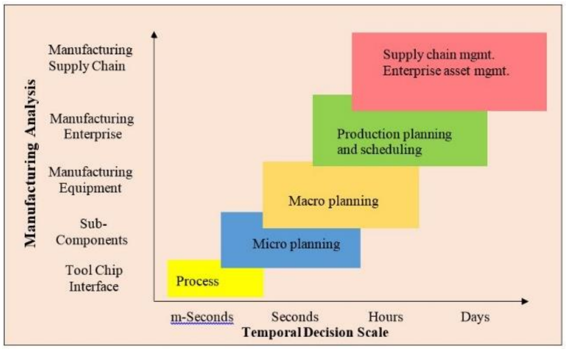

Figure 1: Temporal aspect of decisions and their impact

In manufacturing systems, energy consumption is primarily considered for research in an environmental flow of the system, for 'Life cycle analysis' and other attributes. For example, Dahmus and Gutowski (2004) recorded energy flows while characterizing effects of machining on environment; considering the energy required for chip formation and energy required for operating the manufacturing equipment as two different energies.

Furthermore, taking manufacturing as a system, it is composed of multiple stages, ranging from an elemental stage (unit process) to that of the entire organization. Duflou et al. (2012) enumerated single machine tool as the building block of the manufacturing unit; where cutting time, and process efficiency, based on cutting force and torque is taken as prime factors.

In this research, milling was used as the unit manufacturing process to identify, quantify, and model the initial facets of a broad framework that can measure green manufacturability. Thus, our research focuses on the development of such tools that are capable of monitoring and optimizing the energy consumption during multifaceted manufacturing processes.

1.2 Sustainable Green Manufacturing

Sustainability is frequently defined as: "meeting the needs of the present generation without compromising the ability of future generations to meet their own needs" (Deif 2011). The word "green" symbolizes the awareness towards environment with respect to manufacturing. It depicts the approach in which the manufacturing aspects consider their impact on the environment and resources, and integrate this impact in its overall efficiency, planning, and control. Green manufacturing aims at conserving sustainability's environmental, economical and social objectives in the realm of manufacturing. Sustainable green manufacturing includes controlling hazardous emissions, diminishing uneconomical consumptions of resources and recycling.

Main facets which characterize whether the product is green or not are: environmental effect is lesser than conventional products, the effect is minimal, or it enriches the environment. According to Green Option Matrix developed by Dangelico, and Pierpaolo (2010), a green product consumes less energy as compared to conventional products, and/or it has lesser harmful effects on environment than that of conventional products. For instance Srinivasan and Sheng (1999) evolved an approach for planning feature-based machining at both macro and micro level of planning. In micro planning the process parameters, tooling, and cutting fluid are selected on the basis of process energy use, waste streams, process quality, and machining time. Toenissen (2009) made a detailed investigation of various types of machining process to characterize power consumption of a precision machine tool during a process and it was analyzed empirically. Devoldere et al. (2007) gave the scope of improvement in two types of manufacturing equipment for discrete part production. Productive and non-productive periods are the periods which were classified on the basis of power utilized for the process carried out on a machine tool.

Our work focused on two major aspects of sustainability index, viz., (1) minimizing energy, and (2) minimizing pollution.

1.3 Work environment aspects in manufacturing

In sustainability evaluation, three zones are generally quantified viz. (i) economical, (ii) environmental, and (iii) social. The sphere of social zone covers human safety and societal benefits. Firm owners are liable to provide a safe and healthy environment which includes worker safety, workplace illumination, noise levels etc. For instance, in research, rampant health hazards like hypertension (Chang et al. 2012) and cardiovascular effects (Assunta 2015) have been seen in workers due to high noise levels in manufacturing. Hazards also occur due to aerosol concentration, which is attributed to the particle size and number present in air. Atmadi (2001), Dasch (2005), and Djebara (2013) are amongst the researchers who have contributed in this field.

We considered noise intensity and aerosol concentration as the main factors for this research; impacting the operator health.

1.4 Green manufacturing in milling

In manufacturing, various spheres including quality of product (which is one of the most important parameter to ensure its value) have been given a due consideration in green machining. Better quality can also contribute in limiting the environmental impacts via greater resource efficiency such as shown by Helu et al. (2012).

1.4.1 Green aspects in milling

In present scenario, the application of synthetic metal-working fluids has decreased due to its undesirable impacts on environment, operator's health, and also for economic reasons. This has headed to the use of bio-based metal working fluids as these bio-based or vegetable-based fluids are not only environment friendly but are also sustainable. Their properties like biodegradability, renewability and non-toxic nature have encouraged their use at commendable level. Keeping in mind the above points, an investigation is to be made to study the effects of cutting fluid types taking cutting speed, depth of cut and feed rate as input working parameters, and selected deciding factors. Mathematical models are prepared by researchers, such as by Kuram et al. (2013) using D-optimal technique for process responses. Work on energy consumption as a green aspect has also been reported, for instance by Borgia (2014).

Milling was used as a representative 'unit manufacturing process' in this research. Data was gathered on the aspects of green manufacturing mentioned in previous sections.

1.4.2 Minimum Quantity Lubrication in milling

In Minimum Quantity Lubrication (MQL), cutting fluid is employed at tool-work piece interface as dispersion of fluid droplets with the help of compressed air. Appropriate quantity of fluid and distance between nozzle and tool-work piece interface ends up with the optimal process condition in MQL (Wu and Chein 2007). Also it is observed by Thepsonthi (2009) that the tool wear in case of pulsed jet application is considerable less as compared to that of flood application and dry machining at high cutting speed and low feed rate. Cutting forces in pulsed jet application were lower and surface finish was better as compared to its other two competing methods, whereas tool life in all the application came out to be almost equal. In the same lines, Sales et al. (2009) performed milling operation on AISI 4140 steel using MQL technique and measured tool wear, surface roughness and burr formation using vegetable based cutting fluid at different flow rates. With increase in flow rate of cutting fluid, there is reduction in tool wear, surface roughness and burr length.

In this research, we compared the MQL fluid application technique (mineral and vegetable oils) with other methods of cutting fluid application.

1.5 Manufacturing and simulation

Plentiful techniques, which make use of simulation iterations are available for developing optimal solutions to complex and cumbersome problems in the field of engineering and management. Some examples of applications are Genetic Algorithm (Addona and Teti 2013), Artificial Neural Networks (Addona et al. 2011), and Artificial Bee Colony algorithm (Singh et al. 2015). Artificial bee colony algorithm which is governed by swarm intelligent algorithms, utilizes the intelligence of the comb behavior of swarm to induce solutions for optimizing the problem. This algorithm along with its variants is promising one to cater numerous numerical optimization problems. In experiments; the extended version of Artificial Bee Colony algorithm has surpassed Particle Swarm Optimization

(PSO) and Differential Evolution (DE) as reported by Karaboga and Basturk (2007). ABC literature reveals huge application of ABC in machining.

The simulation in our research was based on ABC technique to numerically develop the optimal solution to the regression models being generated from the experimental data. A greedy algorithm was used for the selection of the algorithm parameters, as described in Singh et al. (2015).

2. Experimental work

The unit manufacturing process of this study had the input variables as cutting speed (V_c), feed (f), and depth of cut (DoC) under four different cooling mediums namely dry, flood, Minimum Quantity Lubrication using 'Servocut-S' mineral oil (MQL_m), and Minimum Quantity Lubrication using 'Canola' vegetable oil (MQL_g). Cutting force (F_c; N), surface roughness (R_a; µm), peak noise intensity (N_{pk}; dB), and aerosol concentration (PM_{10}; µg/m^3) are taken as responses. MQL_m oil is used in distilled water with 8% concentration, and MQL_g is prepared as emulsion, similar to the method suggested by Burton (2014). Duralumin alloy (2024-T351) test coupons having extensive applications in aerospace industries was used as experimental units of size 150 mm × 40 mm × 10 mm. Each experimental unit had wooden packing underneath, and it was mounted on the machine vice, which was in turn mounted on the machine work table, as shown in Figure 2. HSS four flute end mill of 8 mm diameter was used as the tool. F_c values were measured using an online monitoring system with the help of KISTLER rotary dynamometer, type 9123C, and the data was recorded using LabVIEW software. Surface roughness (R_a) was measured using 'Mitutoyo SJ-301 Portable Surface Roughness Tester' for each experiment. Noise intensity was recorded using Extech SDL600 sound level meter with sampling rate set to one second with an 'A' weighting scale (similar to the frequency response of the human ear). LASAIR II particle counter (model 310A) was used for measuring particle size in order to obtain aerosol concentration. The particle counter inlet nozzle was kept at 500 mm from the workstation.

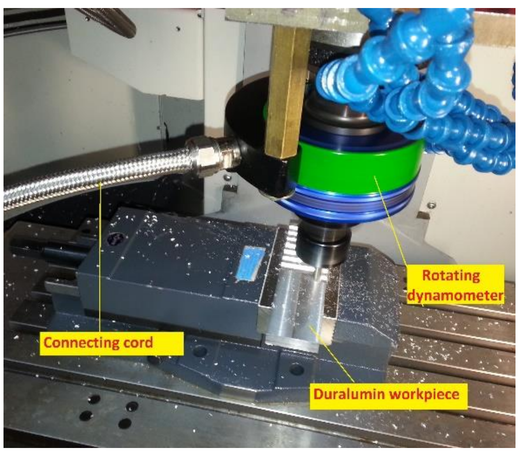

Figure 2 : Dry cutting with EMCO concept mill 250.

Table 1: Cutting conditions (with levels for RSM CCD).

Parameter	Value
Cutting speed, Vc (m/min)	50, 80, 125, 170, and 200.
Feed, f (mm/min)	130, 205, 315, 425, and 500
Depth of cut, DoC (mm)	1, 1.41. 2, 2.59 and 3.
Length of cut	40 mm.
Coolant flow rate	6.5 litre/minute.
MQL flow rate	20 ml/hr

Response Surface Methodology Central Composite Design (RSM CCD) was used for collecting and analysing experimental data. 20 milling experiments in each of the four cooling mediums (dry, flood, MQL_m, and MQL_g) with five levels for each of cutting speed, feed, and depth of cut was conducted, resulting in 320 (20 x 4 x 4) individual experiments. Four replications for each treatment were performed with the end mill and were averaged. Also, a new milling tool was used for each treatment (all four replications). The value of R_a was taken only when the new end mill was used for the first time, resulting in 80 observations. In each of these 80 sample cuts, 10 measuring locations were randomly chosen and measurement was taken in feed direction, and the values were averaged. All equipments were calibrated before the start of the experiments. Table 1 summarizes the cutting conditions used in this study.

3. Results and discussions

As spindle energy is a function of the cutting force; we used it to quantify energy consumed by the unit manufacturing process. Significant changes in process parameters were monitored using surface roughness values. ANOVA was used to identify factors influencing the green index of the process. Tables 2, 3, 4, and 5 summarize ANOVA results for F_c, R_a, N_{pk}, and PM_{10} respectively.

Tables 2 and 3 suggest that speed, feed, and medium of fluid application significantly influence the cutting force and surface roughness. Table 4 depicts that only feed and medium influence peak noise intensity, and Table 5 indicates that only medium of fluid application impacts aerosol concentration.

Table 2 : ANOVA for F_c model using three factors

Source	DF	AdjSS	Adj MS	F-Value	P-Value
Regression	12	5172495	431041	27.58	0.000
V_c	1	75237	75237	4.81	0.032
f	1	81484	81484	5.21	0.026
DoC	1	8505	8505	0.54	0.463
Medium	3	248921	82974	5.31	0.002
V_c*V_c	1	391523	391523	25.05	0.000
f*f	1	23908	23908	1.53	0.220
DoC*DoC	1	115753	115753	7.41	0.008
V_c*f	1	12	12	0.00	0.978
V_c*DoC	1	259908	259908	16.63	0.000
f*DoC	1	257685	257685	16.49	0.000
Error	67	1047036	15627		
Total	79	6219531			

Table 3: ANOVA for R_a model using three factors

Source	DF	Adj SS	AdjMS	F-Value	P-Value
Regression	12	16.7290	1.39408	38.70	0.000
V_c	1	0.7797	0.77967	21.65	0.000
f	1	0.5531	0.55306	15.35	0.000
DoC	1	0.0038	0.00378	0.10	0.747
Medium	3	7.6864	2.56215	71.13	0.000
V_c*V_c	1	1.8064	1.80645	50.15	0.000
f*f	1	1.2754	1.27545	35.41	0.000
DoC*DoC	1	0.0360	0.03600	1.00	0.321
V_c*f	1	0.0278	0.02781	0.77	0.383
V_c*DoC	1	0.0278	0.02781	0.77	0.383
f*DoC	1	0.1620	0.16198	4.50	0.038
Error	67	2.4134	0.03602		
Total	79	19.1424			

Table 4 : ANOVA for N_{pk} model using three factors

Source	DF	Adj SS	AdjMS	F-Value	P-Value
Regression	12	7338.5	611.54	7.44	0.000
V_c	1	57.1	57.13	0.70	0.407
f	1	1959.7	1959.75	23.85	0.000
DoC	1	7.1	7.11	0.09	0.770
Medium	3	1939.8	646.60	7.87	0.000
V_c*V_c	1	317.3	317.35	3.86	0.054
f*f	1	3629.6	3629.61	44.18	0.000
DoC*DoC	1	3.1	3.14	0.04	0.846
V_c*f	1	63.8	63.84	0.78	0.381
V_c*DoC	1	33.2	33.21	0.40	0.527
f*DoC	1	301.4	301.35	3.67	0.060
Error	67	5504.7	82.16		
Total	79	12843.2			

Table 5. ANOVA for PM_{10} model using three factors

Source	DF	Adj SS	AdjMS	F-Value	P-Value
Regression	12	134208564	11184047	164.48	0.000
V_c	1	236094	236094	3.47	0.067
f	1	17547	17547	0.26	0.613
DoC	1	1875	1875	0.03	0.869
Medium	3	133400343	44466781	653.94	0.000
V_c*V_c	1	639053	639053	9.40	0.003
f*f	1	100576	100576	1.48	0.228
DoC*DoC	1	10299	10299	0.15	0.698
V_c*f	1	20105	20105	0.30	0.588
V_c*DoC	1	340	340	0.00	0.944
f*DoC	1	8262	8262	0.12	0.729
Error	67	4555880	67998		
Total	79	138764444			

Regression models were obtained for F_c, R_a and, N_{pk}; with V_c, f, and DoC as independent variables, and 'Medium' as the categorical variable. The resulting model consisted of four equations for the four types of medium. Equations for F_c were:

Dry $$F_c = 1167 - 6.67\,V_c - 2.83\,f - 178\,DoC + 0.04132\,V_c{*}V_c + 0.00168\,f{*}f + 127.2\,DoC{*}DoC - 0.00013\,V_c{*}f - 3.420\,V_c{*}DoC + 1.383\,f{*}DoC \quad (1)$$

Flood $$F_c = 1080 - 6.67\,V_c - 2.83\,f - 178\,DoC + 0.04132\,V_c{*}V_c + 0.00168\,f{*}f + 127.2\,DoC{*}DoC - 0.00013\,V_c{*}f - 3.420\,V_c{*}DoC + 1.383\,f{*}DoC \quad (2)$$

MQL_m $$F_c = 1053 - 6.67\,V_c - 2.83\,f - 178\,DoC + 0.04132\,V_c{*}V_c + 0.00168\,f{*}f + 127.2\,DoC{*}DoC - 0.00013\,V_c{*}f - 3.420\,V_c{*}DoC + 1.383\,f{*}DoC \quad (3)$$

MQL_g $$F_c = 1016 - 6.67\,V_c - 2.83f - 178\,DoC + 0.04132\,V_c{*}V_c + 0.00168\,f{*}f + 127.2\,DoC{*}DoC - 0.00013\,V_c{*}f - 3.420\,V_c{*}DoC + 1.383\,f{*}DoC \quad (4)$$

From the above equations, the MQL_g model has the minimum intercept value in the force (which was also in the case of noise intensity models), which is also evident from Figure 3 (a) and (c). In case of R_a model, flood model has minimum intercept, which was not significantly different from MQL_g model. Hence, only those regression equations for F_c, R_a, and N_{pk}; for the MQL_g case were considered for the optimization stage; considering environmental benefits as well. Also, Figure 4 represents significant interactions depicted in the ANOVA tables. Coefficient of determination (R^2(adj.)) values for this model for F_c, R_a, and N_{pk} were 80.15, 85.13 and 49.46 respectively. Due to poor fit for N_{pk} model, only F_c and R_a models were taken to next stage:

MQL_g $$F_c = 1016 - 6.67\,V_c - 2.83f - 178\,DoC + 0.04132\,V_c{*}V_c + 0.00168\,f{*}f + 127.2\,DoC{*}DoC - 0.00013\,V_c{*}f - 3.420\,V_c{*}DoC + 1.383\,f{*}DoC \quad (5)$$

MQL_g $$R_a = 2.592 - 0.02147\,V_c - 0.00738\,f - 0.119\,DoC + 0.000089\,V_c{*}V_c + 0.000012\,f{*}f + 0.0709\,DoC{*}DoC - 0.000006\,V_c{*}f - 0.00112\,V_c{*}DoC + 0.001096\,f{*}DoC \quad (6)$$

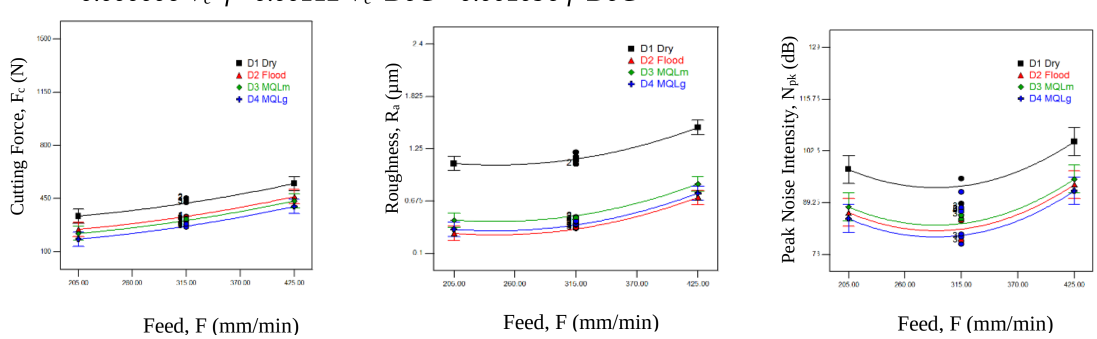

Figure : 3 (a) Cutting force vs feed; (b) Roughness vs feed; and (c) Peak Noise Intensity vs feed; (at V_c= 125 m/min, and DoC = 2 mm)

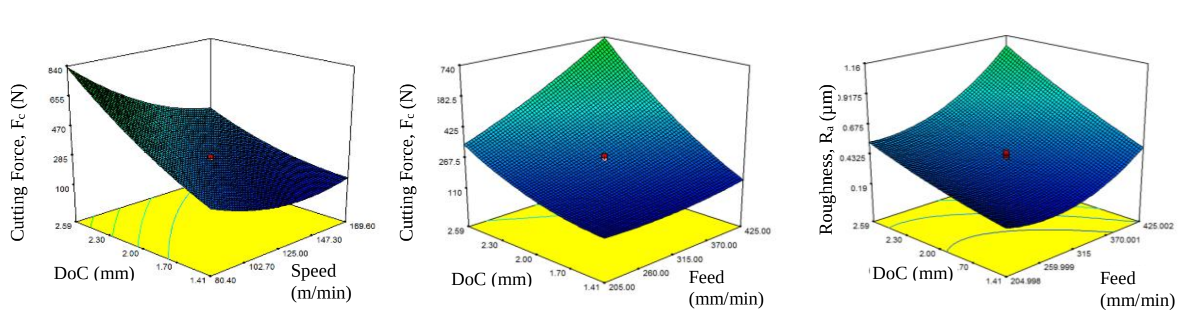

Figure 4: Interactions found significant in the models

Optimization using ABC algorithm for a multi-objective scenario was then conducted by combining the individual models. Weighted-sum method of ABC was used to combine the equations through equivalent scaling of coefficients. The equivalent level scaling of coefficients were conducted using ratio of 1/429 : 1/0.85, where 429 and 0.85 are means of F_c and R_a respectively. However, authors are also working on techniques such as 'Analytical Hierarchy Process' to decide the importance of factors, and assigning appropriate weights.

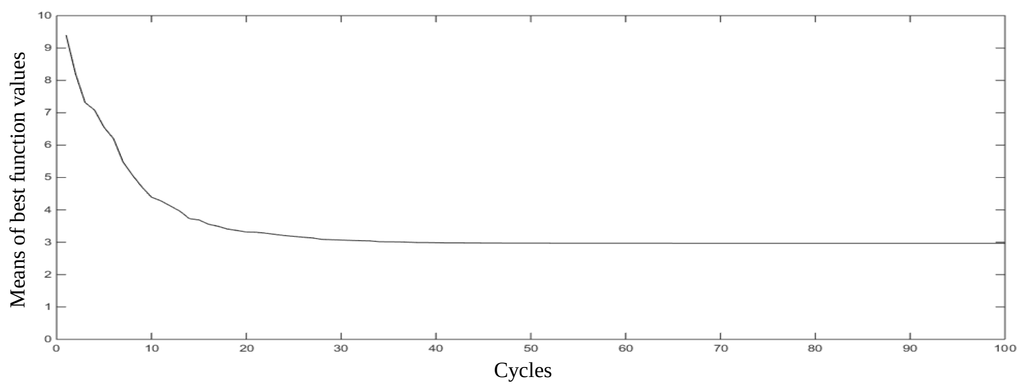

Figure 5: Convergence of ABC algorithm

Before using the ABC algorithm for optimization; initial tuning was done. It is well known that by reducing the swarm size, computation time also reduces. However, it adversely affects the solution quality. After testing for different swarm sizes during tuning; we finalized on swarm size of 10 as an acceptable trade-off between solution time and quality. We also set the ratio of onlooker bees to 50% as per practice reported by other researchers such as Samanta (2001) and Yildiz (2013); who suggested that this ratio provides the ideal trade-off between intensification and diversification to obtain near-optimal solutions. Number of cycles was kept to 1000 to allow for sufficient iterations for the search to converge. Number of runs was set to three to ensure the repeatability of the search. The ABC algorithm outputs for all three replications were consistent: V_c = 130 m/min, f = 327 mm/min, and DoC = 1 mm. The early convergence of the ABC algorithm is shown in Figure 5, suggesting a well behaved experimental data. Sensitivity analysis of the results was conducted with 5 replications, which were within 6% and 4% tolerance for F_c and R_a respectively.

The workplace environment variables, viz., noise intensity, and aerosol concentration can change significantly with medium (high F-value in respective ANOVA Tables 4-5). Figure 3(c) represents variations of noise intensity levels with feed, and the differences in outputs with respect to mediums. High N_{pk} in dry case may be due to chatter at tool-work piece interface at certain instance due to the absence of cutting fluid.

It can be seen from ANOVA Table 6 that medium of fluid application considerably impact (very high F-value) the process. High concentration in the case of MQL_m and MQLg is due to large number of big size (10 µm, or 5 µm dia.) particles. Trial experiments indicated that PM_{10} increases with flow rate (reaches up to 10000 µg/m^3 at 200 ml/hr flow rate) for MQL_m case.

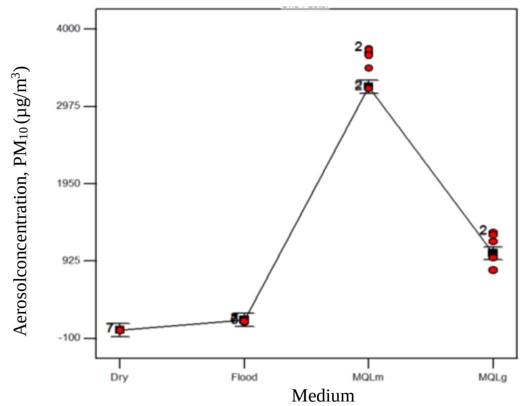

Figure 6 : Aerosol concentration vs medium (at Vc=125 m/min, f=315 mm/min, and DoC=2 mm).

Lesser concentration in MQL_g in comparison to MQL_m may be due to the low viscosity of vegetable oil emulsion in water as shown in Figure 6. Thus, we suggest MQL_g over MQL_m method, so that health hazards associated with mineral oil aerosol can be reduced.

4. Summary

Our research demonstrated that MQL_g method decreased the machining cost through significant reduction in cutting fluid costs, energy costs, and ecological hazards caused from the disposal of non-biodegradable cutting fluids. Besides, factors adversely effecting work environment were also identified. Hence, this approach can be one of the many techniques for improving Green Index of a unit process, and in future of that of a complete manufacturing system.

Also, through this research, optimum settings of the process parameters were determined using ABC simulation. Our approach can be adapted for quantifying the green index of a manufacturing facility, though the results might not be directly transferable. By using discrete event simulation tools such as ARENA, at a factory level green index study is quite possible.

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