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Optimising machining parameters to minimize occupational noise exposure

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Abstract

Need - Metal removal processes are generally optimised to maximise productivity, not minimise noise which is an occupational health risk. There is a need to represent noise in production simulations and minimise it.

Approach - This is addressed by developing a systems dynamics model was developed for machining, including a regression equation for noise, which may be optimised. The benefit of using a regression approach is that it allows a quantification of the complex dependency between noise and process parameters. The benefit of constructing a simulation model is that it provides the tools to optimise noise exposure: i.e. change machine process parameters to reduce noise. This is challenging to do because generally cutting slower or making less deep cuts will reduce noise, but at the cost of worsening the productivity metrics.

Results - For the optimised process parameters, the predicted daily equivalent noise dose was 1.74 dBA, compared to 4.76 dBA for the unoptimised processes. Results show the feasibility of the method, and the ability to reduce noise exposure C_{no}/T_{no} but unfortunately worsening production time.

Contribution –The overall here is piloting a practical methodology for the reduction of noise in a manufacturing environment. This can then be included in a simulation, to calculate occupational noise exposure dose for the multiple machining tasks that make up a realistic production sequence.

Implications for safety practitioners: This work shows a methodology whereby small changes in process parameters, that would not be apparent by causal inspection, may be made to reduce noise.

Future work: Further work is required to achieve a model that cab simultaneously optimise both noise and productivity.

Keywords: machining; noise; productivity; systems dynamics; applied health

1 Introduction and literature

1.1 Health and safety considerations for industrial noise exposure

Health and safety (H&S) is important in machining operations because of the multiple hazards. These hazards include electrical hazards; chemical hazards such as dermatitis from cutting fluids; flying or hot metal chips; cuts from sharp edges; pinch points and crushing injuries; noise; entanglement of loose clothing/hair. Most of these hazards are well contained by existing safeguards. Many machine tools are under computer numerical control (CNC) with enclosures protected by interlocks, thereby reducing the operator's exposure to cutting fluids, containing the machining debris & swarf, avoiding pinch points, and eliminating the entanglement problem. However, noise is difficult to eliminate entirely, because it is transmitted in the air, and the machine enclosures are frequently open at the top. Furthermore, the CNC machines are primarily used in larger volume production settings, or for precise machining of geometrically complex parts, but there is still extensive use of manually controlled (non-CNC) machines for small and specialised tasks in small to medium enterprises (SMEs). These manual machines are seldom enclosed, because to do so would reduce the operator's visibility of the workpiece. Noise is a particularly difficult H&S problem, because the health effects are typically only evident many years later, and may not be possible to attribute to a specific task. Hence there is limited opportunity for continuous or immediate improvement to the working conditions. Also, the effects are cumulative – a small amount of high exposure will not necessarily recover after rest. Furthermore, hearing loss, which is the adverse health outcome from excessive noise exposure, is permanent and only partially treatable with hearing aids. Hearing loss also has a significant social impact, in that elderly people may be unable to communicate effectively with their family and friends, thus decreasing their quality of life.

Hence the analysis of machining noise remains an important safety consideration. Typical industrial practice for H&S practitioners is to use noise meters to assess the sonic environment of the workplace. This is capable of identifying specific machines, which may then be given some treated. Treatments include sound damping barrier materials, moving the machine further away, replacing the machine, outsourcing the task, changing the machine operating parameters, or increasing the quality of the hearing protection (hence personal protective equipment, PPE).

The focus of the present study is changing the machine operating parameters, and the area under study is machining. Metal removal processes are widely used in manufacturing. These processes produce noise, which has safety implications for worker health. Noise depends on cutting parameters such as cutting speed, cutting feed rate, cutting depth, and selection of the appropriate cutting tool type (Wei, Shang, Peng, & Cong, 2022). Generally, these parameters are optimised to maximise productivity, not minimise noise. Most of the methods in manufacturing systems engineering seek to optimise the integration of machines and workers (Leng et al., 2021) by concentrating on layout design, resource allocation, minimisation of task time, and minimisation of non-value-added time. Increasing machine utilisation and productivity generally means operating faster, and this transfers into increased cutting parameters such as faster cutting speed and feed, and deeper cuts. These parameters decrease tool life (Khan, Jaffery, Khan, & Alruqi, 2023), hence productivity can come with an increased cost for consumables. However, the noise intensity also increases and may affect worker health.

There is a need to better understand how noise arises in the manufacturing process, and how to adjust process parameters to reduce the occupational exposure for workers. However, the noise dependency on process parameters and machining conditions (tool wear, coolant, etc.) is complex, and the literature does not show the joint optimisation of productivity and noise. This paper pilots a method to provide such an optimization, albeit limited to optimization of process parameters only. The type of production under examination in this paper is general milling and turning of mild steel.

1.2 Existing approaches to simulation of machining noise

There are numerous of studies on the causes of noise machining operations. Broadly, these studies may be classified into ultra-high speed milling where the focus is usually on minimization of surface roughness (rather than noise per se) and often involving diamond tooling (Otieno, Abou-El-Hossein, Hsu, Cheng, & Mkoko, 2015) (Gregoire, 2021) (Hatefi & Abou-El-Hossein, 2022) (Deng et al., 2023) (Mbangu Tambwe & Pons, 2024), special substrate materials such as aluminium (Kechagias, 2024) or titanium (Shuncai Li, Li, Li, & Chen, 2024) or nickel alloys (Songyuan Li, Li, Liu, & Vladimirovich, 2022), dynamic tool-substrate interactions (chatter) (Sykora, Hajdu, Dombovari, & Bachrathy, 2021; Wang, Zhang, & Hu, 2023) including in thin parts (Y. Lu et al., 2024) and related to vibration (Hu, Li, Deng, & Vadim, 2022), aerodynamic noise of the cutter (C. Ji, Liu, & Ai, 2014) (C. Ji & Liu, 2012), lubrication (Zhenjing et al., 2021), use of noise to infer surface roughness (Shuncai Li et al., 2024) quality including Barkhausen noise methods (Zachert, Schraknepper, & Bergs, 2022) including on, dependency on cutter geometry (Novayer, Wahyudi, Setiono, & Darmawan, 2021) (for wood) or type of insert (Cheng, Wang, Zhao, Wu, & Liu, 2013), noise as a proxy for tool wear status (H. Li, Hao, Dai, & Yang, 2019).

Generally there is an association between noise, vibration, and surface quality because of the dynamic interaction between tool and substrate, and consequently the effect also depends on the process parameters (Rasinac, Petrovi, Radievi, Grkovi, & Ivanovi, 2021). In addition tool geometry parameters such as nose radius and nose angle can affect surface roughness (Balonji, Tartibu, & Okokpujie, 2023) and accuracy (Guo & Sun, 2021), and hence also noise.

Historically noise has been a secondary consideration to roughness and operational productivity. However, more recently noise has become something that needs to be managed in its own right (Rech, Dumont, Le Bot, & Arrazola, 2017). This is because of occupational health and safety duties, and the need to minimise deafness later in life. There is also the problem of passive noise exposure for workers other than the machine operator. The biological effects of noise exposure are difficult to predict as deafness is typically a late-onset cumulative phenomenon, that is difficult to attribute to a single event or employment situation (Z. Ji, Pons, & Pearse, 2021). Consequently, there is a need to minimize the noise exposure throughout the operating plant.

The parameters that most affect milling noise have been identified by (Rech et al., 2017) as part stiffness (aluminium), mill diameter, cutting speed, feed and axial depth, with radial depth of cut not being sensitive.

The ISO 8525 standard describes methods for testing noise emitted by metal cutting machines (Wegener, Bleicher, Heisel, Hoffmeister, & Möhring, 2021). Many machines emit more than 85 dBA (Teixeira et al., 2021). Among the loudest machines are rapid stamping and weaving machines (Guo & Sun, 2021). In metal industry, the experienced sound levels averaged over a nominal working daily time of 8h vary between 84.1dBA to 100.4 dBA (L. Zhou et al., 2022).

The frequency of noise is also important. Machining metal noise has a frequency range of 22 Hz to above 10kHz (Shankar, Manikandan, Raja, & Pramanik, 2020). In the audible range, the sound power spectrum peaks at about 500Hz to 10kHz. Many machines produce noise in the range of 1,600 Hz to 4,000 Hz, which is the sensitive human hearing range (Wegener et al., 2021). Currently, insufficient noise prevention in the industry is an occupational hazard for millions of people (Mahapatra, Satapathy, Panda, & Panigrahi, 2023). Hearing loss occurs due to damage of the cilia (hair cells) in the inner ear. Human hearing covers the range of about 20Hz to 20kHz, with most speech in the range 50Hz to 7kHz. Hence it is important to limit occupational exposure to frequencies in the hearing range. Hearing loss continues to be a problem despite attempts at mitigating it (Hunter et al., 2020). Quantifying and monitoring sound levels in industry is one of the solutions (Sinay, Balážiková, Dulebová, Markulik, & Kotianová, 2018). Weighting filters are used on the raw dB to represent the effect on the human body (Shehap, Shawky, & El-Basheer, 2015).

In the literature, many different approaches have been applied to decrease noise intensity in industry. Models of noise in industrial plants have been attempted, particularly from the perspective of mapping the noise signal for an existing factory layout (L. Lu, Kurfess, & Saldana, 2021). This may also be represented as a numerical simulation(Bozkurt & Demirkale, 2017; Han, Haron, Yahya, Bakar, & Dimon, 2015). However modelling noise as part of an industrial productivity simulation, and the joint optimisation of productivity and noise, does not appear in the literature. There is no study on the processing of noise using a systems dynamics approach.

2 Method

2.1 Research objectives

The objective of this research was to optimise process parameters to minimise noise in a routine machining process (milling and turning or mild steel), while also minimising the adverse effect on operational productivity. By optimisation is meant the minimisation of the noise exposure (weighted daily dose received by the operator), and the optimisation criteria are the process parameters. While there are many process parameters that affect noise production in machining, the key universal set are fed, speed, and depth of cut, and these are selected for optimisation. In general, there can be expected to be some combination of the process parameters that gives least noise emissions, but the problem is that this might result in an excessively slow machining process, i.e. the process takes longer, and productivity worsens. To address this, it is also necessary to check on material removal rate.

This study does not explore the effects of other factors known to be associated with noise production: type or grade of material, tool geometry, tool coatings, or coolant.

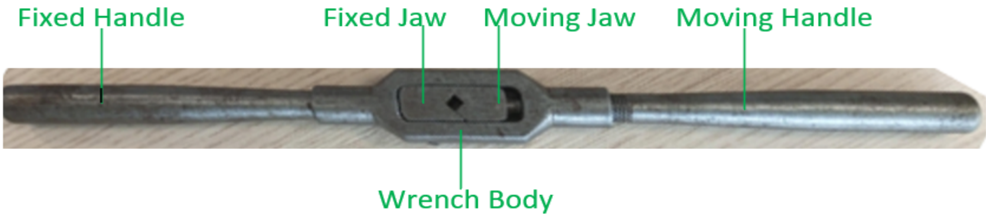
2.2 Production environment

The production environment under examination is a training workshop for students where the operation is to create a tap wrench.

Workpiece

A metal removal process was selected, in the form of a tap wrench made by engineering students as part of their course work as shown in Figure 1. There are three processes involved: turning, drilling and milling.

Figure 1: Tap Wrench



Workpiece material

The type of material used to manufacture a tap wrench was Mild Steel. The material properties are specified in Table 1.

Table 1: Workpiece material specification.

Mild Steel	
Density	7850kg/m3
Ultimate Tensile Strength	400 – 550 MPa
Yield Strength	250 MPa
Young's Modulus of Elasticity	200GPa
Brinell Hardness	120BHN
Melting Point	1450 ºC
Thermal Conductivity	50W/mK
Heat Capacity	510J/gK

Workshop equipment

The workshop used Colchester lathes (Student 2500). Lathe Turning Tools comprised metal turning tool holders with 16mm shanks and carbide tool tips (designation WNMG 3-2 TF IC 830). The milling machines were turret vertical types (KING RICH Industries Co., model KR-V3000SL), using end-mill cutters diameter 50 mm with 5 carbide tips (model Viper Bit manufactured by Sutton Tools Industry). Drill bits were jobber Drill Blue 5 mm and Jobber Drill Black Jet 11.50mm, high speed steel from the same manufacturer as for end-mill cutters. The carbide tools are assumed to be sharp and retain their operational capabilities over the duration of the tests. As the substrate material is mild steel, this is a reasonable assumption.

2.3 Approach

2.3.1 Determine metal removal

Mass measurement: The mass was measured using a KERN digital scale (Model FCB, Gottl KERN & Sohn GmbH) for the raw and finished part. From this, the volume of material for the raw and finished were computed.

Time of operation (T_{OP}): The total machining time for each part was determined by the expert technician in charge of the facility. Within each part there are multiple machined features, and the times for these were determined from calculated material removal rates.

Material removal rate: Material Removed (MR) represents material removed by each machining operation and Material Removal Rate (MRR) (Ayabaca & Vila, 2020) refers to the volume per unit time:

$$\boldsymbol{MRR} = \frac{\boldsymbol{W_{chip}\ x\ A_{chip}}}{\boldsymbol{T}}\ [\boldsymbol{mm^3/s}] \tag{1}$$

With W_{chip} = With of chip (mm), A_{chip} = The cross-sectional area of chip (mm^2),

$T = \text{Time of the operation}(s)$

The following equations apply per (Ayabaca & Vila, 2020):

Turning:

$$\boldsymbol{MRR} = \boldsymbol{D_p * F_r * V_c} \tag{2}$$

With D_p= Cutting Depth, F_r= Cutting Feed rate, V_c= Cutting speed

Milling:

$$\boldsymbol{MRR = D_p * D_r * V_f} \tag{3}$$

With D_p= Cutting axial depth, D_r= Cutting radial depth, V_f= Cutting speed

Drilling:

$$\boldsymbol{MRR = \frac{1}{4}(D * F_r * V_c)} \tag{4}$$

With D= Drill diameter, F_r= Cutting Feed rate, V_c= Cutting speed

Equation (5) gives Time of operation:

$$\boldsymbol{T_{OP} = \frac{MR}{MRR}} \tag{5}$$

2.3.2 Development of a systems dynamics model

These processes were then modelled in ANYLOGIC software (version 8.9.0 Anylogic Company - Formerly XJ Technologies) to determine a predicted time for each operation for each part. The simulation approach used system dynamics (SD).

The model was constructed to represent the flow of material removed for tap wrench parts during the machining operation. The following assumptions were made in constructing the model. For each metal removal step, the machining coefficient represents the proportion of mass removed (MR) to get the part into the next operational state. MR is linked to the i^{th} and $(i-1)^{\text{th}}$ transitory manufacturing stage and is flowing to the chip pan.

Application of the MRR results in an ideal (shortest) removal time, e.g. *MillingB1* involves removal of 650 mm^3 at a MRR of 10,000 mm^3/min hence an ideal removal time of 0.065 min. assuming a single pass. In practice the measured time is 19 min. This large difference is attributed to set-up time, tool return path, and the need for multiple paths. In the corresponding SD model, the computed time is 8.01 minutes, which was determined by setting the measured time for the whole part (167 min total machining time for Body).

2.3.3 Development of a model for machining noise

There were two parts to this stage. In in the first part, algorithms for noise as a function of the primary process parameters (speed, feed, depth of cut) were developed for each of turning, milling, and drilling operations. The turning algorithm was fitted from data in the literature.

The milling and drilling algorithms were determined from experiments conducted in the workshop. A design of experiment (DoE) approach was taken to determine combinations of process parameters. Both milling and drilling operations were on mild steel, using the same machines, and lubricant conditions as used for the tap wrench. Noise levels were measured, see Appendix A for raw data.

Also, allowable noise exposure was obtained from the literature. In the second part, noise was measured for real operations.

2.3.4 Algorithm for noise as a function of process parameters

Predicting production noise level from process parameters (feed, speed, depth of cut) is a complex problem that is incompletely addressed in the literature (Turkkan et al., 2023) (Rech et al., 2017) (Rasinac, Radičević, Kolarevic, Petrović, & Bjelić, 2021). For conventional machining of steel, it is known that noise level (NL, dBA) is dependent on these cutting factors (Shaikh, Ali, Khan, & Asjad, 2023). The precise relationship is not clearly established in the literature, at least not for all the factors that may affect noise. Noise has been investigated for milling (Rasinac, Radičević, et al., 2021), but with only depth of cut as variable. At least in high speed machining spindle speed has been identified as a non-significant factor (Deng et al., 2023). Feed rate is probably important, since in conventional machining of steel, it is known that the material removal rate (MRR, cm^3/min), surface roughness (Ra, μm), resultant cutting force (F, Newton), and noise level (NL, dBA) are highly dependent on feed rate (Shaikh et al., 2023).

To predict noise from all three parameters (feed, speed, depth of cut) is a more complex problem. The optimization approach taken here requires a fitness function expressed algebraically, and this may be met by use of three regression equations. However, such a model could not be found in the literature. The only exception was (Shaikh et al., 2023) where raw data were reported in a form conducive to creating such an turning equation (though the regression equation was not explicitly provided in the source). The milling and drilling models have been established from experimented data from workshop students at university of canterbury, see Appendix A.

Turning

Our reanalysis of (Shaikh et al., 2023) shows that machining noise in turning (mild steel, data measured at 500 mm from source) may be expressed by a regression equation of the form:

$$\textbf{Noise level NL}\ (\textbf{dBA}) = \mathbf{70.267 + 0.028 * \boldsymbol{v} + 17.639 * \boldsymbol{d} + 12.611 * \boldsymbol{f}} \qquad \text{(6a)}$$

with

$\boldsymbol{v}$: Cutting speed (mm/min), $\boldsymbol{d}$: Cutting depth (mm), $\boldsymbol{f}$: Cutting feed rate (mm/rev)

The data from (Shaikh et al., 2023) were apparently based on a design of experiments approach, with a single data point for each set of parameters. All the data were used for the regression equation, and no attempt was applied to identify or exclude outliers as the results were all experimentally measured values. The Adjusted R^2= 0.991 is a good degree of fit, which gives confidence that (a) outliers were not a significant issue, and (b) the noise dependency can reasonably be assumed to be linear.

This analysis shows that depth of cut is the most influential parameter, followed by feed rate, and then cutting speed, and that all are statistically significant, see Figure 2. The linear regression results are shown in Table 2. These show a good degree of fit (Adjusted R^2= 0.991, F (3,23) = 935.350).

Figure 2. Statistical reanalysis of (Shaikh et al., 2023) identifying key parameters.

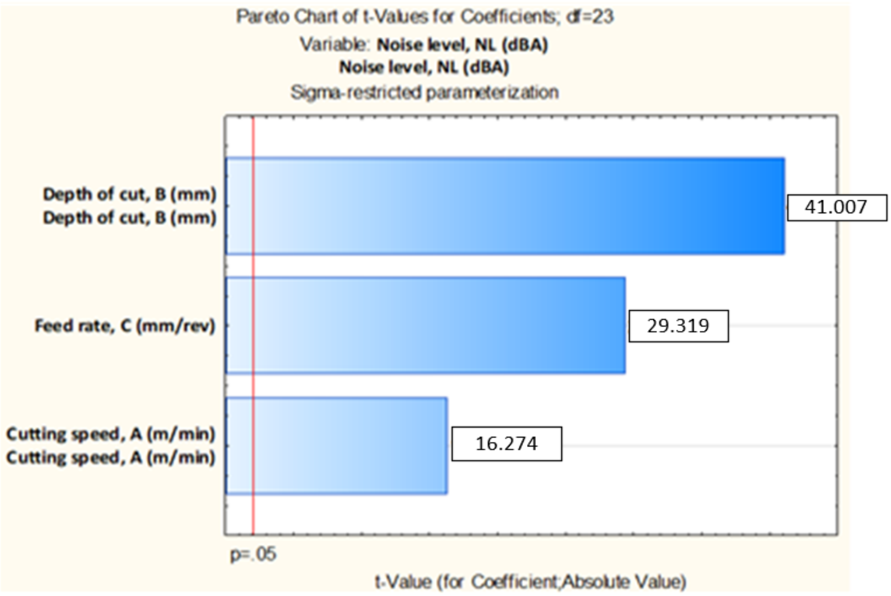


Table 2.a: Model coefficients for noise.

N=27	Regression Summary for Dependent Variable: Noise level, NL (dBA) R= 0.996, R^2= 0.992, Adjusted R^2= 0.991, F(3,23)=935.350, p<0.000, Std.Error of estimate: 0.365					
	b*	Std Err	b	Std. Err	F(3,23)	p-value
Intercept			b_0 =70.267	0.547	128.380	0.000
Cutting speed, v (m/min)	0.306	0.019	b_1 = 0.028	0.002	16.274	0.000
Cutting Depth d (mm)	0.771	0.019	b_2 =17.639	0.430	41.010	0.000
Cutting Feed rate f (mm/rev)	0.551	0.019	b_3 =12.611	0.430	29.320	0.000

Note that the b values are the coefficients in the original units, hence used in the model regression equation. In contrast b* is standardised to remove the effect of the different scales for the input variables, hence shows the relative importance of the different input variables (as number of standard deviations to get one standard deviation change in the output variable).

Milling

The analysis of data shows that machining noise in milling may be expressed by a regression equation of the form:

$$\textbf{Noise level NL (dBA)} = \mathbf{65.020 + 0.051 * v + 6.833 * d_a + 0.014 * f} \quad (6b)$$

with

v : Cutting speed (m/min), d_a: Cutting axial depth (mm), f : Cutting feed (mm/min)

Table 2.b: Statistical analysis of identifying key milling parameters.

N=27	Regression Summary for Dependent Variable: Noise level, NL (dBA) R= 0.829, R²= 0.687, Adjusted R²= 0.646, F (3,23)=16.830, p<0.0001, Std.Error of estimate: 1.774					
	b*	Std Err	b	Std. Err	t(23)	p-value
Intercept			$b_0 = 65.020$	1.731	37.554	0.000000
Cutting speed v, (rpm)	0.673	0.117	$b_1 = 0.051$	0.009	5.765	0.000007
Cutting Axial Depth d_a, (mm)	0.381	0.117	$b_2 = 6.833$	2.091	3.268	0.003382
Cutting feed f, (mm/min)	0.299	0.117	$b_3 = 0.014$	0.006	2.564	0.017367

As it was for turning model, the b values are the coefficients in the original units, hence used in the model regression equation.

Drilling

The analysis of data shows that machining noise in milling may be expressed by a regression equation of the form:

$$\textbf{Noise level NL (dBA)} = \mathbf{53.512 + 0.021 * v + 24.018 * f + 1.115 * d} \quad (6c)$$

with

v: Cutting speed (rpm), f: Cutting feed rate (mm/rev), d: Drill diameter (mm)

Table 2.c: Statistical analysis of identifying key drilling parameters.

N=27	Regression Summary for Dependent Variable: Noise level, NL (dBA) R= 0.838, R²= 0.702, Adjusted R²= 0.663, F(3,23)=18.038, p<0.000, Std.Error of estimate: 3.039					
	b*	Std Err	b	Std. Err	t(23)	p-value
Intercept			$b_0 = 53.512$	2.632	20.335	0.000000
Cutting speed v, (rpm)	0.561	0.114	$b_1 = 0.021$	0.004	4.926	0.000056
Cutting Feed Rate f, (mm/rev)	0.222	0.114	$b_2 = 24.018$	12.338	1.947	0.063893
Drill diameter d, (mm)	0.581	0.114	b_3 =1.115	0.218	5.104	0.000036

2.3.5 Noise exposure

Noise exposure is a complex combination of the sound level and duration of exposure (Chen, Su, & Chen, 2020). Allowable noise exposure was adopted from (Hager, 1998; J. Zhou, Shi, Zhou, Hu, & Zhang, 2020):

$$\boldsymbol{Noise\ exposure} = \sum_{i=1}^{p} \frac{C_{ni}}{T_{ni}} \quad (7)$$

With p: Real number, i : Machining operations

Where:

C_n: The total time of exposure at a specific noise level [hr]

$$C_n = \frac{T_{machining}}{60} \quad (8)$$

$\boldsymbol{T_n}$: The reference time duration [hr]

$$\boldsymbol{T_n = \frac{8}{2^{(NL-90)/5}}} \quad (9)$$

Noise dose (D)

$$\boldsymbol{D = 100 * Noise\ exposure = 100 * \sum_{i=1}^{p} \frac{C_{ni}}{T_{ni}}} \quad (10)$$

2.3.6 Noise measurement for real operations

Noise level was measured for the machining operations for the tap wrench. Noise was measured using a “Professional Sound Level Meter” (QM1598) in a workshop with hard reflective surfaces, at a distance of 50 mm from the machine during the machining operations. The accuracy class of the noise meter is ± 0.01 dBA. One repetition of noise measurement was performed for each machining operation. Peak noise level was determined over the full duration of the task.

3 Results

3.1 Mass and volume for raw and finished parts

Difference of measured raw and finished material masses is material removed during Tap Wrench machining. The last in short time produced the noise exposure which was applied as objective function for optimisation approach. The volume of raw, finished and removed material have been computed using density of steel mild accordingly. This was eventually used with machining coefficient to compute operational time. Table 3 shows the details.

Table 3: Mass and volume for raw and finished parts and material removed.

Parts	Measured			Steel Mild Density [g/mm3]	Material removed. [mm^3]
	Mass raw material [g]	Mass finished part [g]	Material removed. [g]		
Wrench Body	524.0	139	385.0	0.00785	49,045
Fixed Jaw	71.6	31	40.6	0.00785	5,172
Moving Jaw	143.3	33	110.3	0.00785	14,051
Fixed Handle	240.0	185	55.0	0.00785	7,006
Moving Handle	240.0	173	67.0	0.00785	8,535

To machine the tap wrench in the student workshop, the technician in charge has elaborated a data with input factors as shown in Table 4. During machining, cutting parameters were used to machine each part of Tap wrench separately. Cutting speed was in rpm, cutting feed rate in mm/rev and cutting depth in mm.

Table 4: Cutting parameters, measured machining times and measured noise. The ‘operation’ refers to the machining sub-tasks and is defined in the simulation results.

Operation	Cutting Speed	Cutting Feed Rate	Cutting Depth	Cutting axial depth	Cutting radial depth	Work piece Diameter	Tool Diameter	Measured Time	Measured noise
	(rpm)	(mm/rev)	(mm)	(mm)	(mm)	(mm)	(mm)	(min)	(dBA)
Body									
MillingB1	800			0.250	0.5	Not applicable	50	5.4	95.80
MillingB2	800			0.250	0.5	Not applicable	50	6.8	95.80
MillingB3	800			0.250	0.5	Not applicable	50	7.5	95.80
MillingB4	800			0.250	0.5	Not applicable	50	7.8	95.80
DrillingBody1	540			0.038		Not applicable	11.5	11.3	92.10
DrillingBody2	450			0.038		Not applicable	5	31.2	91.80
TurningBody	1,750	1.25	0.50			16.6		9.4	88.56
Fixed Handle									
FacingFH	850	1	0.05			16.6		5.0	73.00
TurningFHA	1,500	1.25	0.05			16.6		6.5	72.20
TurningFHB	1,200	1.25	0.05			16.0		7.2	74.50
TaperingFH	375	1.25	0.10			16.0		4.6	82.50
Moving Handle									
FacingMH	850	1.000	0.05			16.6		4.2	74.00
TurningMHA	1,500	1.250	0.05			16.6		7.3	74.60
TurningMHB	1,200	1.250	0.05			16.0		7.8	83.30
TaperingMH	375	1.250	0.10			16.0		4.9	81.60
DrillingMH	750	0.152					7.5	5.5	80.10
Fixed Jaw									
MillingFJ1	800			0.500	0.25	Not applicable	50.0	4.7	98.11
MillingFJ2	800			0.500	0.25	Not applicable	50.0	4.2	99.35
MillingFJ3	800			0.500	0.25	Not applicable	50.0	5.5	75.20
Moving Jaw									
MillingMJ1	850			0.500	0.25	Not applicable	50.0	5.5	98.29
MillingMJ2	700			0.500	0.25	Not applicable	50.0	6.5	98.24
MillingMJ3	800			0.500	0.25	Not applicable	50.0	6.0	98.24
TurningMJ	1,500	1.250	0.50			7.5		8.0	108.87

3.2 Machining coefficient k_i

The machining coefficient k_i represents the proportion of material remaining after a machining stage, see Table 4. For example, for the Body part the machining stages (i) are MillingB1; MillingB2; MillingB3; MillingB4; DrillingBody1; DrillingBody2; TurningBody. In this table, the material removed in each operation was determined by weighing the part, after which the removed volume was calculated using known density.

Then the machining coefficient for stage i is the following general expression:

$$k_i = V_i / V_{i-1} \quad (11)$$

Where V_i : The volume of machined part at the i^{th} manufacturing stage.

V_{i-1}: The volume of workpiece before machining

This expression has been developed per Table 5 and conducted on the expression (12).

$$k_i = 1 - \frac{(MR)_i}{RawM - \sum_{i=1}^{n}(MR)_{i-1}} \quad (12)$$

Where $RawM$: Raw material of workpiece

$(MR)_i$: Material removed at i^{th} manufacturing stage.

$(MR)_{i-1}$: Material removed at $(i-1)^{\text{th}}$ manufacturing stage

n : The total number of operations.

Table 5: Machining coefficients $\boldsymbol{k_i}$

PARTS	Operation	Material removed. [mm^3]	Machining coefficient $\boldsymbol{k_i}$						
			k_1	k_2	k_3	k_4	k_5	k_6	k_7
Body	MillingB1	649.90	0.99						
	MillingB2	9,718.80		0.85					
	MillingB3	3,840.00			0.93				
	MillingB4	112.00				0.99			
	DrillingBody1	9,874.00					0.81		
	DrillingBody2	8,386.98						0.80	
	TurningBody	16,463.30							0.52
Fixed Handle	FacingFH	1,004.80	0.97						
	TurningFHA	2,226.42		0.92					
	TurningFHB	3,516.80			0.87				
	TaperingFH	257.90				0.99			
Moving Handle	FacingMH	1,004.80	0.97						
	TurningMHA	2,226.42		0.92					
	TurningMHB	3,516.80			0.87				
	TaperingMH	257.90				0.99			
	DrillingMH	1,529.08					0.95		
Fixed Jaw	MillingFJ1	1,905.00	0.79						
	MillingFJ2	2,483.00		0.66					
	MillingFJ3	784.00			0.83				
Moving Jaw	MillingMJ1	1,905.00	0.99						
	MillingMJ2	2,483.00		0.85					
	MillingMJ3	3,815.40			0.72				
	TurningMJ	5,847.60				0.42			

Hence the material removed in each machining stage may be represented as:

$$MR_i = M_i(1 - k_i) \quad (13)$$

3.3 System dynamics model

3.3.1 Architecture of the systems dynamics model

SD was applied, and the model was structured as follows. Each tap wrench part was separately modelled and simulated. The way the model operates is as follows: for each operation i, cutting parameters are given, and used to calculate material removal rate MRR_i per equations (2-4) (grey box). The material removed MR_i is modelled by Equation (13) (pink box). Then the time and noise level are calculated as $T_i = MR_i / MRR_i$ and noise level as Equation (6) and noise dose is eventually computed with Equation (10) consecutively. The SD model iterates towards solving this problem. Nonetheless there are advantages in doing it with a systems dynamics model because this shows the system as a causally closed structure defining its specific actions, it may also discover the system's feedback loops which balance or reinforce the result. Furthermore, this simulation tool can identify stock levels and flows. The stock can represent the machined part state between two operations, while flows are materials removed state which become rates with states change in time.

The rationale behind the selection of the machining sequence for each part is based on considerations of how the part is to be held in a dimensionally stable attitude to receive the tooling. This dictates that, in this the example of *Tap wrench body* which is a flat-sided finished part, it is first necessary to mill a reference surface (hence MillingB1 is the first machining operation). There are number of different approaches to this (e.g. MillingB2 could be the start point), and hence the sequence presented here is not necessarily unique, but it is practical. In most cases the results are not particularly sensitive to the order of machining operations. Similar considerations apply to the other parts, e.g. turning usually commences with a facing operation.

Results follow for each part in the assembly, showing the part itself, the system dynamics model that computes the production time and noise, and a brief description of the findings. Details about the model construction are provided in Appendix B, and detailed results in Appendix C\.

3.3.2 Tap wrench body

The machining cuts necessary to produce this part are shown in Figure 3, as a series of machining operations (MillingB1, then MillingB2, etc.).

The SD model is given in Figure 4 and shows the machining sequence and the computation for noise exposure.

Figure 3: Body machining operations

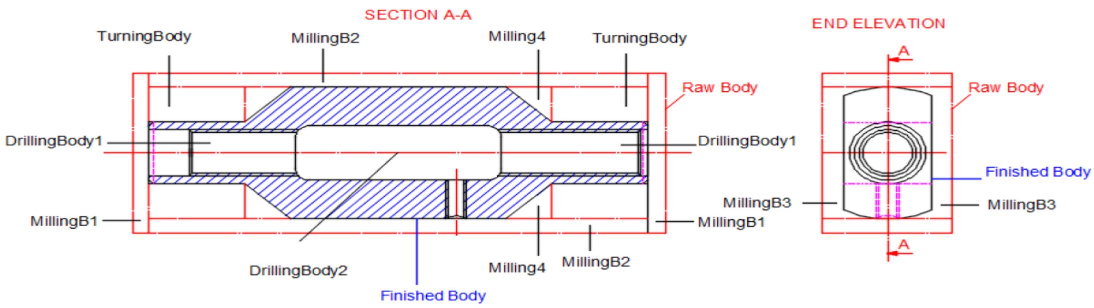
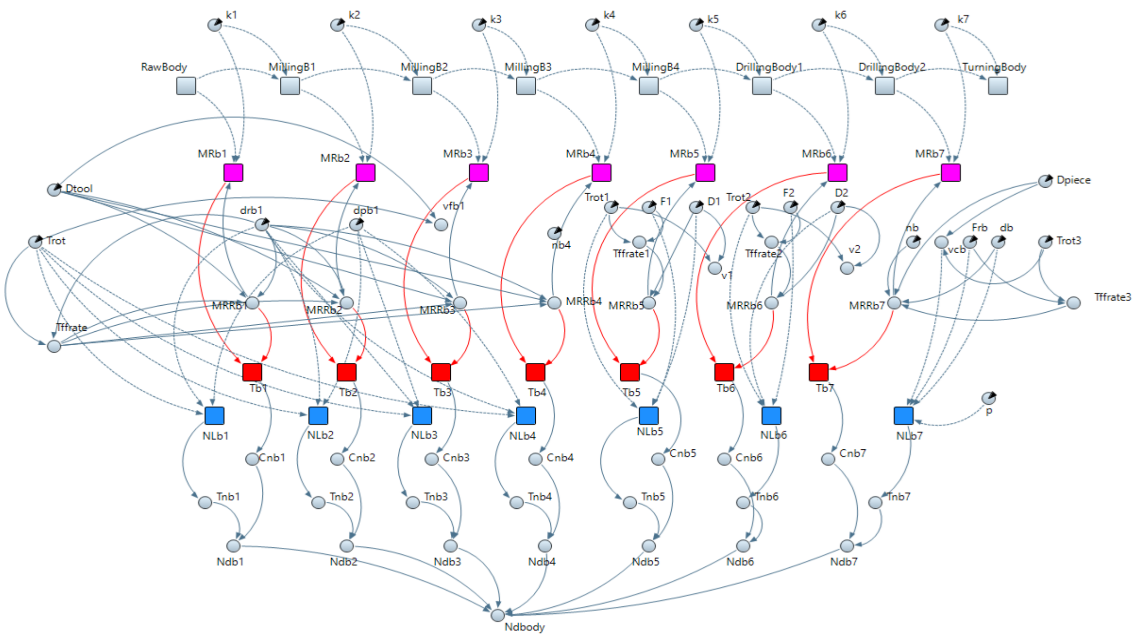


Figure 4: System Dynamic Body model with Anylogic.



In the SD model the top row (grey blocks) represents the stages in the machining process, as defined in Figure 3. The MRn series (pink boxes) computes the material removal, and the material removal rate is shown in MRRn (grey boxes). The operation time is determined in Tn (red boxes). Cutting parameters are speed (n*), depth of cut radial (dr*), depth of cut axial (dp*), cutting speed (v*), feed rate (F*).

The results for the tap wrench body are shown in Table 6. The simulated times are not close to the measured values for all tasks. However, for MillingB2, MillingB3, DrillingBody1 and TurningBody there is a large set-up time or difference time. This is attributed to the need to set up the part, set up the machine (including find the datum & position the tool), make the cuts (in several passes), and repeat for the other side of the part. This is the first milling task performed by the students, so they are cautious and on the early part of the learning curve.

For the first drilling action (task 5, DrillingBody1) the measured time is much longer than the simulated time. This is attributed to the need to take the workpiece out of the mill, clean up the mill, and reset it in the drilling station. In addition, the actual drilling action has more complexities than the simulation captures, because it involves a drilling down the whole of the long axis of the part. Hence the part must be securely fixed, which takes time. In addition, the student workers proceed very cautiously regarding feed rate. Hence the operation takes much longer than the idealised simulation.

For the final turning operation (task 7, TurningBody), the simulated time is again much less than the actual. This is attributed to the extra time required to set up the four-jaw chuck (which is included at this point as a training exercise for students).

All machining operations show lower removal times values. However, this attribution is the fact that machining operation only represents 15% of the whole production cycle time. Furthermore, MillingB4, removal time is very low, this is credited to few removed quantities.

Computed and removal material noises levels are the same for all the milling tasks (1-4), highest for the drilling task (5), and lowest for the turning task (7). Drilling is higher, probably because of great diameter tool and high cutting depth. Turning is also intense for noise because of high cutting parameters.

3.3.3 Fixed handle

The machining cuts necessary to produce this part are shown in Figure 5, and the SD model for time and noise is given in Figure 6. The MR1 to MR4 are computed material removal, and the material removal rate is shown in MRR1 to MRR4. T1 to T4 represent operation time. Cutting parameters are pass number (n*), depth of cut radial (dr*), depth of cut axial (dp*), cutting speed (v*), feed rate (F*).

Figure 5: Fixed Handle machining operations

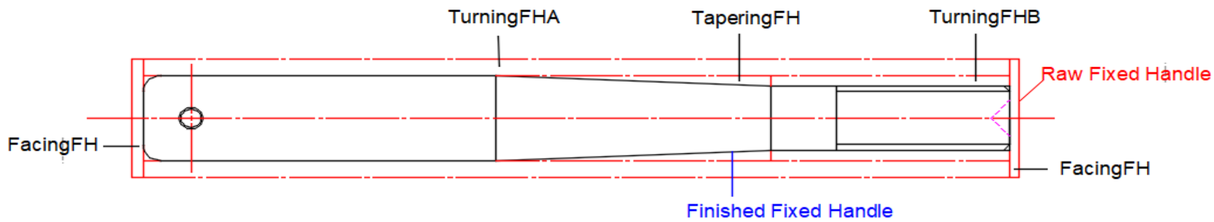
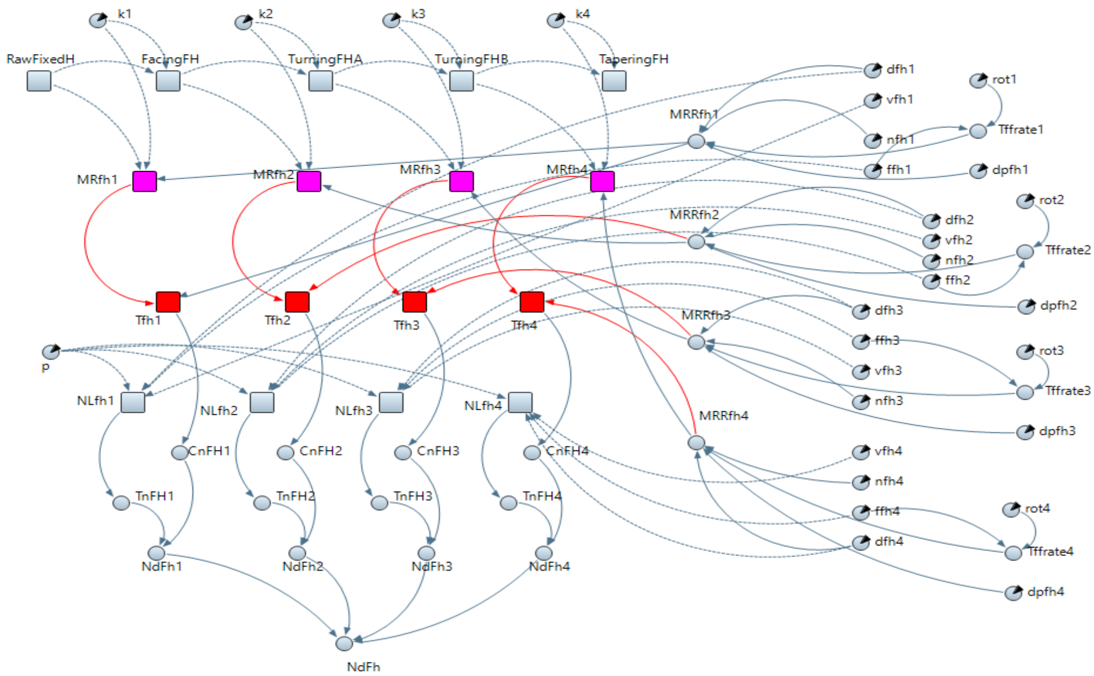


Figure 6: System Dynamic Fixed Handle model with Anylogic



Fixed handle was machined following the operations such as facing, turning, and tapering. Presenting cylindrical form, turning operation recurrence has twice occurred then facing and tapering. Table 6 shows that the simulated times are not close to the measured value for all tasks while they are closest removal times which are very small. Further, the measured value for task turningFHA is the highest compared to computed time and removal time, their difference conducts to highest setting time value. For the all turning operations, the setting times are again much high because the operational use of a four-jaw chuck that does not self-centre the workpiece. Moreover, measured NL value is lowest for turningFHA operation because of lowest cutting depth for measurement and computational approaches and speed while all show the highest value of NL for taperingFH due to higher cutting depth. Increasing cutting feed rate increases NL for turningFHB.

3.3.4 Moving handle

The machining cuts necessary to produce this part are shown in Figure 7, and the SD model for time and noise is given in Figure 8. Cutting parameters are pass number (n), depth of cut (dp), depth of cut axial (dpD), cutting speed (v), feed rate (F).

Figure 7: Moving Handle machining operations

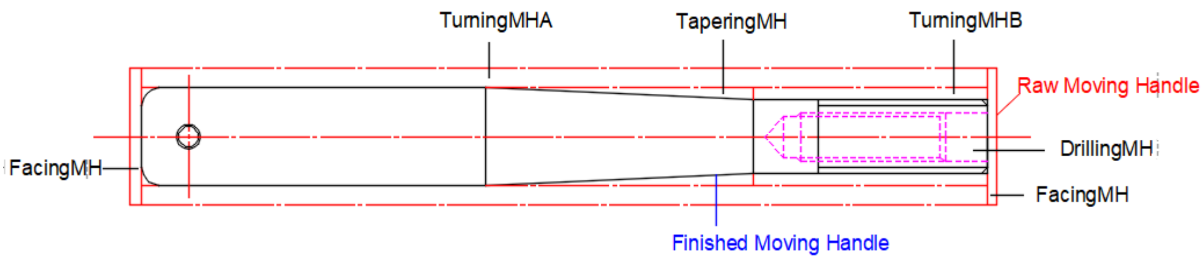
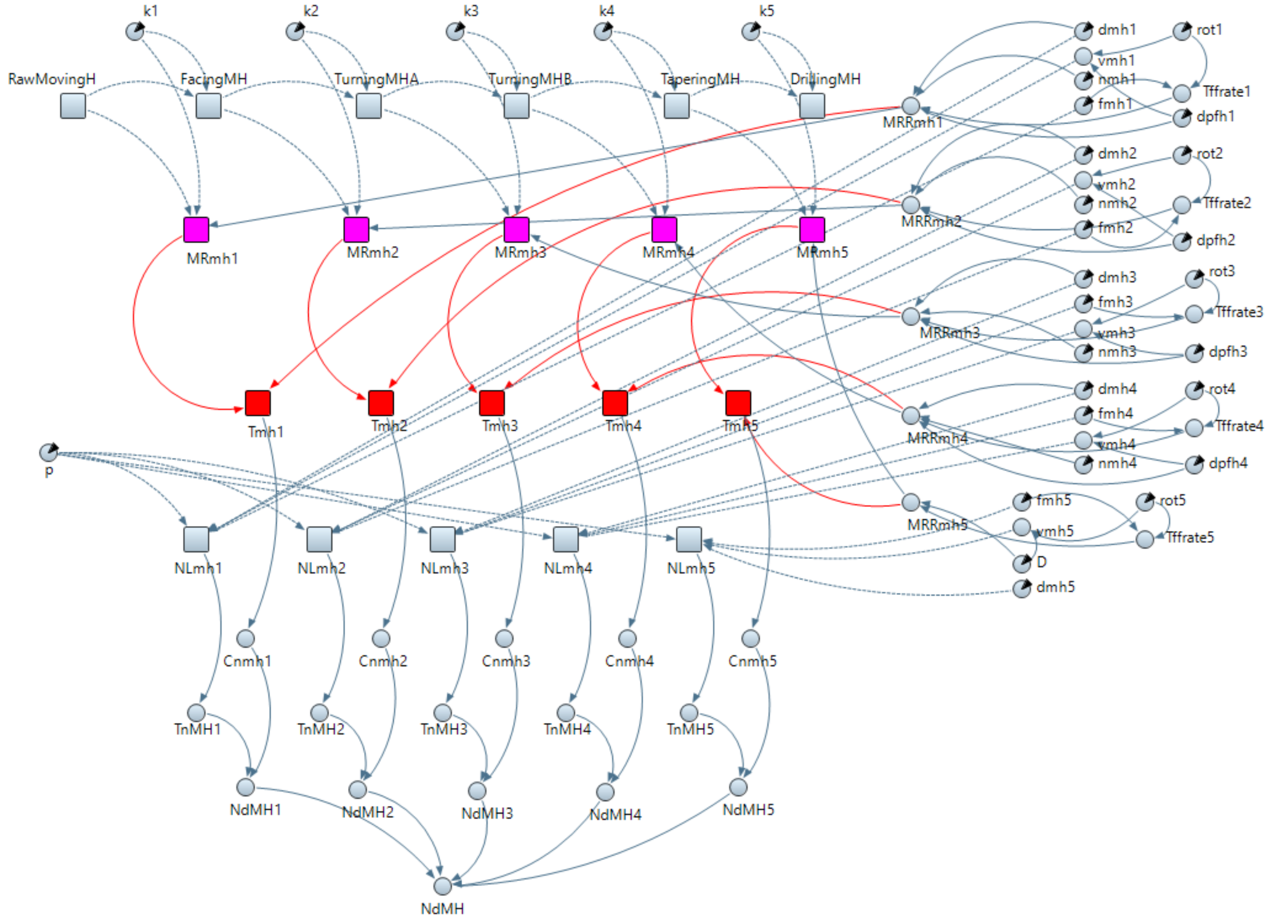


Figure 8: System Dynamic Moving Handle model with anylogic



The results for the tap wrench Moving handle are shown in Table 6. The simulated time is close to the removal time value for tasks of facingMH and turningMHB. While removal time is far to be close and has lower time for taperingMH. Measured time is higher for turningMHA because there is a large set-up time inference including number of passes.

Lower NL value is for the task facingMH because of minimal cutting depth and speed while the task taperingMH has higher value NL due to increasing cutting speed and depth for computed and removal material noise levels. For the task turningMHA, the NL rises because of increasing cutting speed and reducing cutting feed rate while cutting depth is kept. For turningMHB, reducing cutting speed and increasing cutting feed rate increase measured NL compared to turningMHA for both methods. Comparatively to facing task, drilling task has high NL due to the processing lower cutting speed, high cutting feed rate and depth.

3.3.5 Fixed jaw

The machining cuts necessary to produce this part are shown in Figure 9, and the SD model is given in Figure 10. Cutting parameters are pass number (n), depth of cut radial (dr), axial depth of cut axial (dp), and cutting speed (v).

Figure 9: Fixed Jaw machining operations

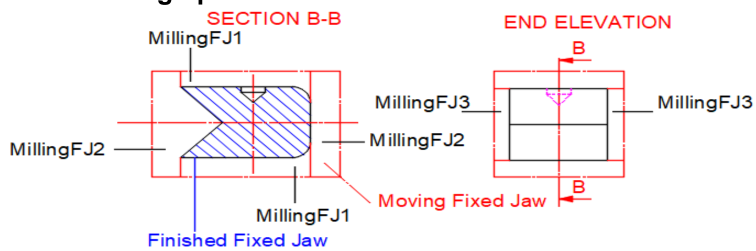
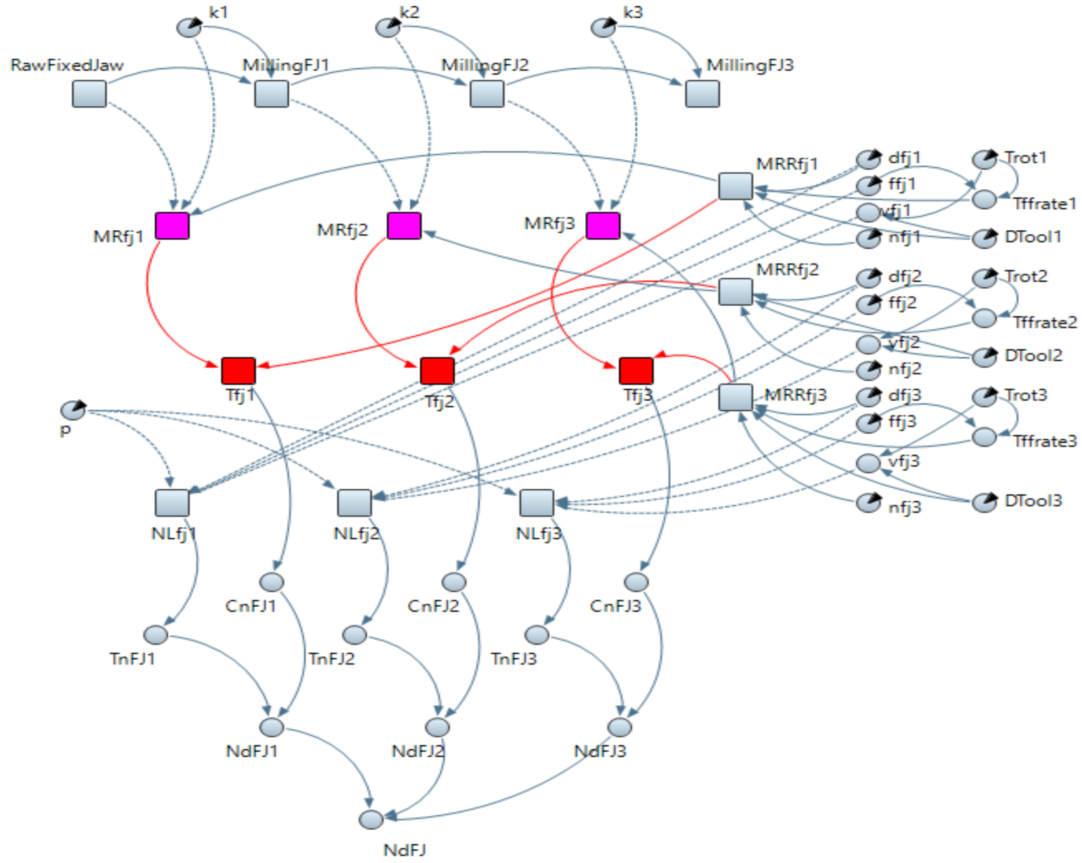


Figure 10: System Dynamic Fixed Jaw model with anylogic



The results for the tap wrench fixed Jaw are shown in Table 6. The removal times are lower than measured and simulated times. Tasks MillingFJ1 and MillingFJ3 are approximate but the millingFJ2 task time remains the highest for computational approach while measured and removal material time are the lowest comparatively. For the third milling action (task 3, MillingFJ3) the measured time is much long than all times. This is attributed to set-up time to take the workpiece out of the mill. In addition, the milling action is more complex than the simulation captures, due to the secure fixing and tuning number of passes. Additionally, the student workers proceed very cautiously regarding cutting depth. Thus, the operation becomes much longer than for the computation. In addition, measured and computed NL values are lowest for millingFJ3 due to minimal cutting depth and feed rate. Because of the one rotation of this part, setting time is too short for millingFJ2 task, but there is emission of higher NL value because of high cutting depth and feed rate while the cutting speed is kept for all tasks. Finaly, millingFJ1 has second high NL value after the task 2.

Cutting parameters resulted on default machining noise and taken noise exposure dosage for fixed jaw, see Table 6. Analysis of these results is given with more details in this Table, such as higher noise exposure dosage is higher for measured approach and lower for removed material approach during their reference durations.

3.3.6 Moving jaw

The machining cuts necessary to produce this part are shown in Figure 11, and the SD model is given in Figure 12. Cutting parameters are pass number (n), depth of cut radial (dr), axial depth of cut axial (dp), and cutting speed (v).

Figure 11: Moving Jaw machining operations.

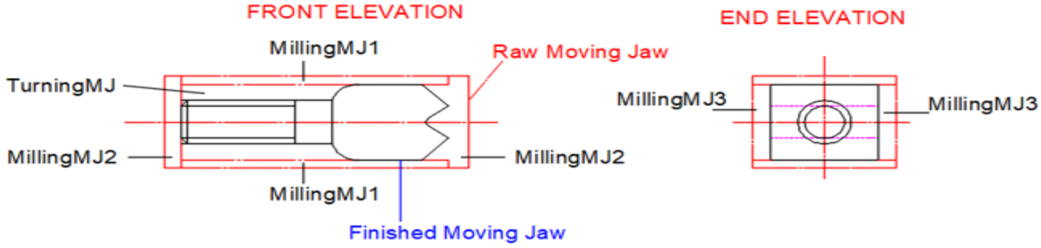
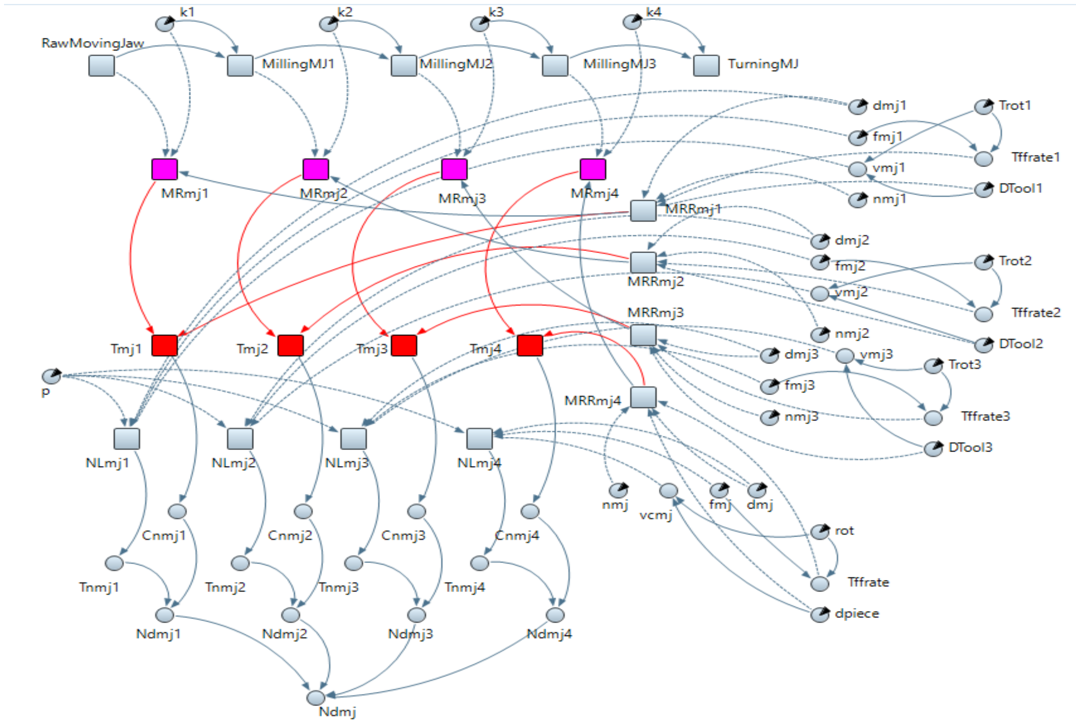


Figure 12: System Dynamic Moving Jaw model



Machining of moving Jaw involved 3 milling and 1 turning operations. The results for this part of tap wrench are given in Table 6. The simulated times are not close to the measured values for millingMJ2 and TurningMJ tasks while removal times are lower due to proper machining. However, for TurningMJ, there is a large, implied set-up time. This is due to set up the part on the milling machine and make the cuts with several passes. While task millingMJ2 has short setting time, this is because of one rotation of workpiece on milling machine.

High NL value is presented by millingMJ3 due to high cutting feed rate and depth, Whereas, reduced cutting feed rate and low cutting speed conduct to minimum NL value for turning task. As shown by Table 6, low cutting feed rate and high cutting depth result on third high NL value after the task 2 that is due to second high cutting depth and seventy five percent of task 3 cutting feed rate.

3.4 Simulation results for machining time, noise level, and noise exposure of Overall model

The noise level produced by each operation was measured in the workshop and also calculated using the noise regression equation forementioned. The total noise exposure across all operations depends on the total time of exposure at a specific noise level C_n per equation (8), and equations (9) and (10) presents reference time duration Tn, and noise dose. In all cases the noise dose is without hearing protection. There are two sets of critical parameters in the calculation of noise dose. The first is the dependency of operation noise on cutting parameters. The second is the dependency of total noise dose on the duration of machining time for each operation. Significant differences arise in the machining time, depending on the way it is determined, and these affect the noise dose.

3.4.1 Methods for determining machining time

Three ways of determining machining time were included. These are:

(A) Measured Time. This used a stopwatch. The results include setup, machining time, and a variety of non-value-added times. This the most realistic time, but it is difficult to separate out the components.

(B) Time computed using Anylogic. This time uses the machining coefficients, material removed, and material removal rates. This result is believed to more accurately represent the machining-only component of the work.

(C) Time calculated from first principles of material removal rate. This result is typically much less than the other values. It ignores all set up and number of passes, and instead assumes perfect efficiency in machining.

3.4.2 Tabular results

The results are shown in Table 6 (a, b). As expected, the noise doses for A-C above, are very different. For measured time 35.11 dBA, for Anylogic computed times 4.76 dBA, and for MRR calculation 4.98 dBA. This large difference is an artefact of the way of determining machining time, and is not an issue in what follows, where the Anylogic approach is used consistently throughout. Calculated milling noise results are markedly higher than measured. This is attributed to the nature of the milling metal removal process being different to other operations, particularly that the milling cutting edge does have a higher velocity.

Table 6: Simulation results.

(a) Cutting parameters, measured machining times, computed time, setting time.

	Material removed (mm3)	Machining	Tool & piece rotation (rpm)	Tool & piece Diam (mm)	Cutting Feed Rate & Cutting radial depth (mm/rev)	Cutting axial depth (mm)	Tip Cutting Speed Vc=pi*D*N (mm/min)	Tip Cutting speed (m/min)	Tool forward Feed Rate (mm/min)	MRR (mm3/min)	Measured machining Time (min)	Anylogic Computed machining Time (min)	Material Removal Time (min)	Inferred Set up Time (min)
Body														
MillingB1	650	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	5.4	0.134	0.13	5.27
MillingB2	9719	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	6.8	1.983	1.94	4.86
MillingB3	3840	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	7.5	0.788	0.77	6.73
MillingB4	112	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	7.8	0.104	0.02	7.78
DrillingBody1	9874	Drill	540	11.50	0.038		19,499.00	19.50	20.52	2,130.31	11.3	4.856	4.64	6.66
DrillingBody2	8387	Drill	450	5.00	0.038		7,065.00	7.07	17.10	335.59	31.2	24.657	24.99	6.21
TurningBody	16463	Turning	1750	16.60	1.250	0.50	91,217.00	91.22	2187.5	57,039.54	9.4	0.280	0.29	9.11
											79.4	32.802	32.78	46.62
Fixed Handle														
FacingFH	1005	Sise facing	850	16.60	1.000	0.05	57,650.40	57.5626	1700.00	4,432.79	5.0	0.414	0.45	4.55
TurningFHA	2226	Turning	1,500	16.60	1.250	0.05	78,186.00	78.19	1875.00	4,889.10	6.5	0.486	0.46	6.04
TurningFHB	3517	Turning	1,200	16.00	1.250	0.05	60,288.00	60.29	1500.00	3,769.91	7.2	0.941	0.93	6.27
TaperingFH	258	Tapering	375	16.00	1.250	1.25	18,840.00	18.84	468.75	29,452.43	4.6	0.008	0.01	4.59
											23.3	1.849	1.85	21.45
Moving Handle														
FacingMH	1005.00	Side facing	850	16.60	2.000	0.05	57,650.40	57.65	1700.00	4,432.79	4.2	0.414	0.45	3.75
TurningMHA	2226.00	Turning	1,500	16.50	1.250	0.05	78,186.00	78.19	1875.00	4,889.10	7.3	0.486	0.46	6.84
TurningMHB	3517.00	Turning	1,200	16.00	1.250	0.05	60,288.00	60.29	1500.00	3,769.91	7.8	0.941	0.93	6.87
TaperingMH	258.00	Tapering	375	16.00	1.25	1.25	18,840.00	18.84	468.75	29,452.43	4.9	0.008	0.01	4.89
DrillingMH	1529.00	Drill	750	7.50	0.152		17,662.50	17.66	114	5,033.81	5.5	0.233	0.30	5.20
											29.7	2.082	2.15	27.85
Fixed Jaw														
MillingFJ1	1905.00	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	4.7	0.380	038	4.32
MillingFJ2	2483.00	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	4.2	0.490	0.50	3.70
MillingFJ3	784.00	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	5.5	0.162	0.16	5.34
											14.4	1.032	1.03	13.37
Moving Jaw														
MillingMJ1	1905.00	Side milling	850	50.00	0.250	0.50	133,450.00	133045	212.5	5,312.50	5.5	0.034	0.36	5.14
MillingMJ2	2483.00	Side milling	700	50.00	0.250	0.50	109,900.00	109.90	175	4,375.00	6.5	0.620	0.57	5.93
MillingMJ3	3815.00	Side milling	800	50.00	0.250	0.50	125,600.00	125.60	200.00	5,000.00	6.0	0.860	0.76	5.24
TurningMJ	5848.00	Turning	1,500	7.50	1.250	1.25	35,325.00	35.33	1,875.00	55,223.31	8.0	0.116	0.21	7.79
											26.0	1.630	1.30	24.10
Totals											172.80	39.400	39.72	133.08

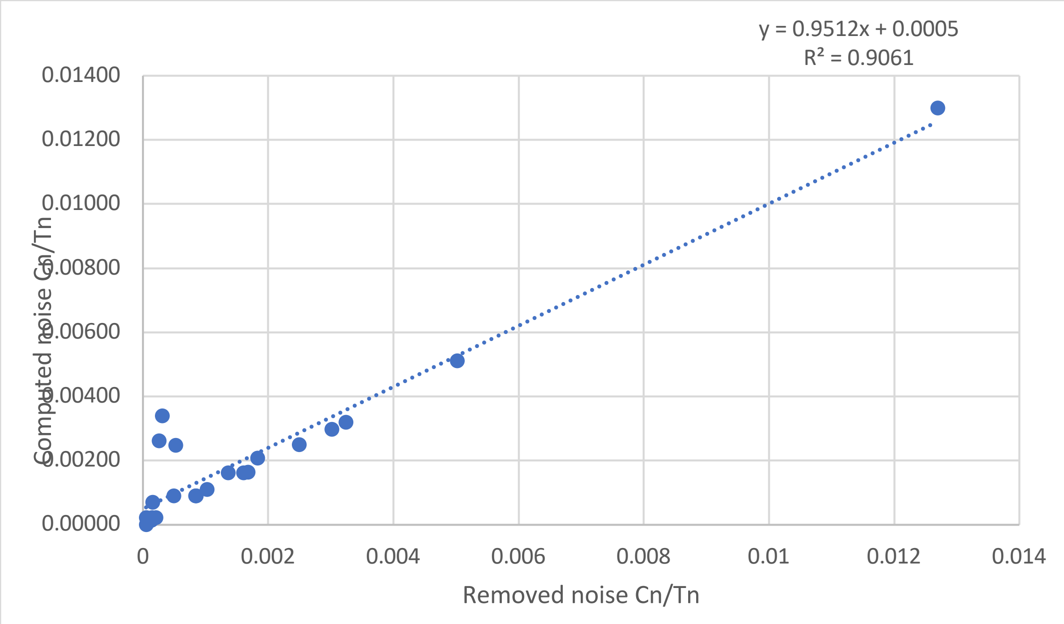
(b) Measured, Computed, removed material noise level and noise dose with no hearing protection.

	Measured Noise Level (dBA)	Cnm (dBA)	Tnm (hrs)	Noise exposure Cnm/Tnm (dBA/100)	Anylogic Computed Noise Level (dBA)	Cnc (hrs)	Tnc (hrs)	Anylogic Computed Noise exposure Cnc/Tnc (dBA/100)	MRR Noise Level - Noise calculated per Eqn 13 with Cnr and Tnr calculated from material removal rate (dBA)	Cnr (hrs)	Tnr (hrs)	MRR Computed Noise exposure Cnr/Tnr (dBA/100)
Body												
MillingB1	95.80	0.0900	3.58	0.0251	98.24	0.0022	2.552	0.000875	98.24	0.0022	2.552	0.00085
MillingB2	95.80	0.1133	3.58	0.0317	98.24	0.0331	2.552	0.012951	98.24	0.0324	2.552	0.01269
MillingB3	95.80	0.1250	3.58	0.0349	98.24	0.0131	2.552	0.005146	98.24	0.0128	2.552	0.00502
MillingB4	95.80	0.1300	3.58	0.0363	98.24	0.0017	2.552	0.000679	98.24	0.0004	2.552	0.00015
DrillingBody1	92.10	0.1883	5.98	0.0315	768.59	0.0809	38.924	0.002079	78.59	0.0773	38.923	0.00198
DrillingBody2	91.80	0.5200	6.23	0.0834	69.46	0.4110	138.141	0.002975	69.45	0.4165	138.147	0.00302
TurningBody	88.56	0.1567	9.77	0.0160	77.40	0.0047	2.866	0.001628	97.40	0.0048	2.866	0.00168
			36.30	25.8982 dBA			190.140	2.633385dBA			190.14	2.53840 dBA
Fixed Handle												
FacingFH	73.00	0.0833	84.45	0.0010	97.99	0.0069	2.645	0.002609	97.99	0.0069	2.644	0.00261
TurningFHA	72.20	0.1083	94.35	0.0011	89.10	0.0081	9.061	0.000984	89.10	0.0081	9.061	0.00089
TurningFHB	74.50	0.1200	68.59	0.0017	88.60	0.0157	9.712	0.001615	88.60	0.0157	9.713	0.00161
TaperingFH	82.50	0.0767	22.63	0.0034	108.61	0.0001	0.607	0.000220	108.61	0.0001	0.607	0.00022
			270.02	0.7273 dBA			22.024	0.533781dBA			22.024	0.53378dBA
Moving Handle												
FacingMH	74.00	0.0700	73.52	0.0010	97.61	0.0069	2.785	0.002478	97.99	0.0076	2.644	0.00286
TurningMHA	74.00	0.1217	67.65	0.0018	89.10	0.0081	9.061	0.000894	89.10	0.0076	9.061	0.00084
TurningMHB	83.00	0.1300	21.11	0.0062	88.60	0.0157	9.712	0.001615	88.60	0.0155	9.713	0.00160
TaperingMH	81.60	0.0817	25.63	0.0032	108.61	0.0001	0.607	0.000220	108.61	0.0001	0.607	0.00024
DrillingMH	80.10	0.0917	103.97	0.0009	81.28	0.0039	26.816	0.000145	81.28	0.0051	26.815	0.00019
			291.88	1.2976 dBA			48.980	0.535113dBA			48.839	0.57251dBA
Fixed Jaw												
MillingFJ1	98.11	0.0783	2.60	0.0301	98.24	0.0063	2.552	0.002482	98.24	0.0064	2.552	0.00249
MillingFJ2	99.35	0.0700	2.19	0.0320	98.24	0.0082	2.552	0.003201	98.24	0.0083	2.552	0.00324
MillingFJ3	75.20	0.0917	62.25	0.0015	98.24	0.0027	2.552	0.001058	98.24	0.0026	2.552	0.00102
			67.04	6.3596 dBA			7.655	0.674039dBA			7.656	0.67557dBA
Moving Jaw												
MillingMJ1	98.29	0.0006	2.54	0.0002	75.27	0.0006	61.632	0.00009	74.87	0.0060	65.155	0.00009
MillingMJ2	98.24	0.0090	2.55	0.0035	74.07	0.0103	72.797	0.000142	74.87	0.00095	65.155	0.00015
MillingMJ3	98.24	0.0070	2.55	0.0027	74.87	0.0143	65.155	0.000220	74.87	0.0127	65.155	0.00020
TurningMJ	108.87	0.0010	0.58	0.0017	109.07	0.0019	0.569	0.003398	109.06	0.0035	0.570	0.00620
			8.22	0.8220 dBA			200.152	0.385296dBA			196.034	0.66289 dBA
TOTALS			673.47	35.1046 dBA			468.951	4.76155dBA			464.70	4.98316 dBA

3.4.3 Validation of noise results

Scatter plot of the individual noise doses (Cn_i/Tn_i) for computed vs. calculated from material removed shows a reasonable degree of fit (R^2=0.9061), see Figure 13.

Figure 13: Degree of fit for computed vs. measured noise doses



3.4.4 Production time and noise exposure for the default process the whole product

For the whole product, the production noise was calculated with the reference time duration of the default process. This was calculated for total project duration (Sum of task durations) or whole machining of the tap wrench. The amount of noise exposure dosage (C_{nc}/T_{nc}) for default machining process was 4.76 dBA in the duration of 468.951 hours. Whereas measurement approach results to the noise exposure dosage of 35.11 dBA in 673.47 hours and removed material approach results to the noise exposure dosage of 4.98 dBA with the duration of 464.70 hours .

3.5 Optimisation of Machining Noise level

It is desirable to reduce noise, for workshop safety. This can be achieved by optimising the cutting parameters. The optimisation was performed using Anylogic and considering the objective function limit value as requirement. This part of the optimisation process determined the machining parameters for minimised noise, using the noise regression equation.

3.5.1 Optimisation process

The objective function was the noise equation (13), which was minimised. The parameters to be optimised were *Cutting Speed, Cutting Feed Rate, Cutting Depth.* Range intervals with minimum**,** maximum values and step were applied to cutting parameters for calibration. Total production noise was required to be equal or near to 4.76dBA which is the total value of noise calculated anylogic.

Noise function for each component was used as optimizing objective. To run this objective function, the number of iterations was fixed, and all parameters were given an arbitrary range encompassing the data in Table 4, with random seed. Total measured time of each component was used as model stop time. All constraints and requirements were checked after simulation to determine whether solution feasibility.

3.5.2 Results of optimisation

Each processing operation has a computed machining time (T) which leads to a total time of exposure at a specific noise level given in hours (C_{no}). The reference duration [hrs] for each noise exposure is used to compute the noise dose, see Table 7. The total noise dosage (C_{no}/T_{no}) represents noise during the total machining time. Optimizing procedure of the noise level by changing the cutting parameters, may also affect the wear and durability of the cutting tool, and hence also productivity. For example, for Body in the MillingB1 – MillingB4 operations, tool rotation velocity is reduced 1.6 times, and cutting feed rate and depth are reduced by 1.02 and 3.1 times successively. Although wear was not explicitly calculated, it generally correlates with noise and total cutting distance.

Table 7: Optimised cutting parameters values

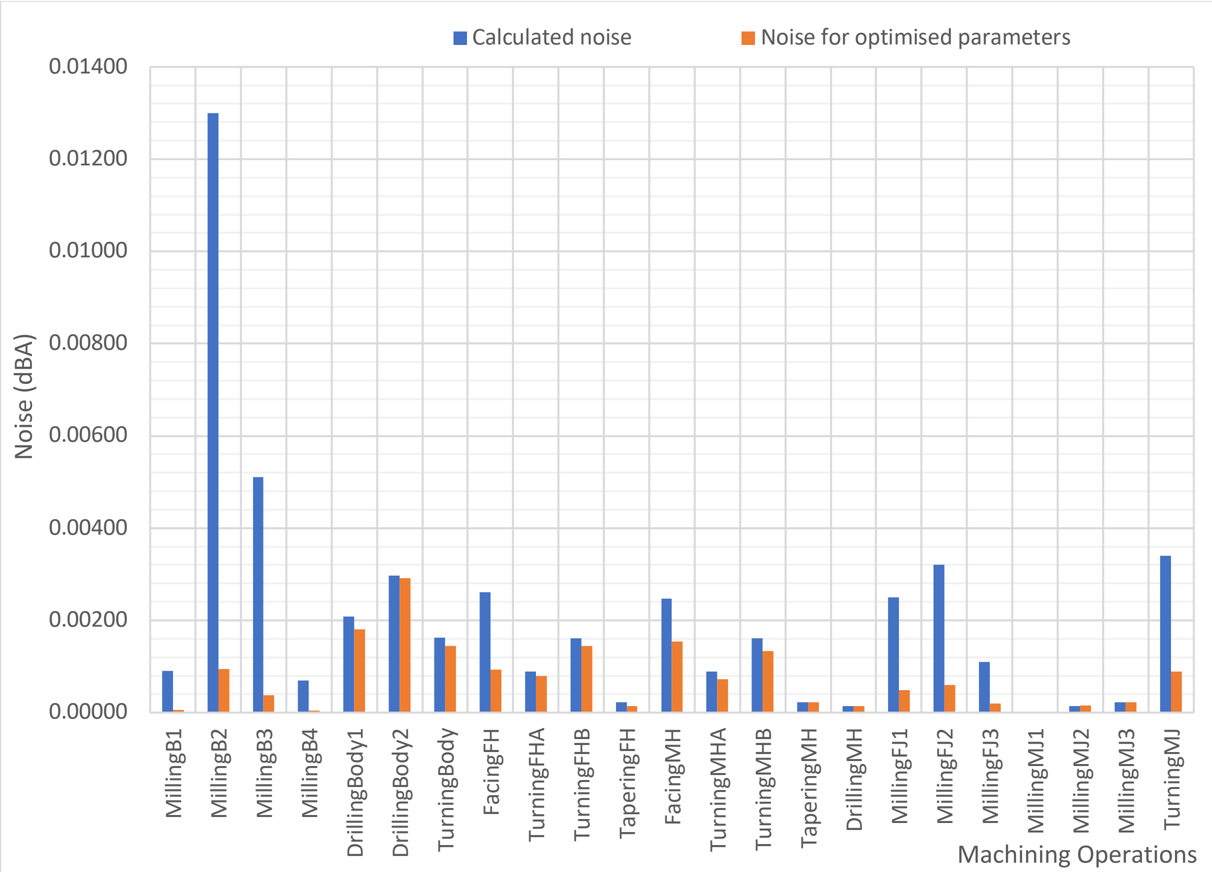
	Material removed	Machining	Tool & piece rotation(rpm)	Tool & piece Diam (mm)	Cutting Feed Rate & Cutting axial (mm/rev)depth	Cutting Depth (mm)	Tip Cutting Speed Vc=pi*D*N (mm/min)	Tip Cutting speed (m/ min)	Tool forward Feed Rate (mm/min)	MRR (mm3/ min)	Machining Time Computed with Anylogic (min)	Optimised Anylogic Computed Noise Level (dBA)	Cno (hrs)	Tno (hrs)	Cno/Tno (dBA /100)
Body															
MillingB1	650	Side milling	500.00	50.00	0.246	0.164	78500.16	78.50	123.00	1008.60	0.66	67.88	0.011	171.71	0.00006
MillingB2	9719	Side milling	500.00	50.00	0.246	0.164	78500.16	78.50	123.00	1008.60	9.83	67.88	0.164	171.71	0.00095
MillingB3	3840	Side milling	500.00	50.00	0.246	0.164	78500.16	78.50	123.00	1008.60	3.90	67.88	0.065	171.71	0.00038
MillingB4	112	Side milling	500.00	50.00	0.246	0.164	78500.16	78.50	123.00	1008.60	0.52	67.88	0.009	171.71	0.00005
DrillingBody1	9874	Drill	434.31	11.50	0.038		15683.01	15.68	16.50	1713.37	5.74	76.37	0.096	52.94	0.00181
DrillingBody2	8387	Drill	376.40	5.00	0.038		5909.51	5.91	14.30	280.70	29.85	67.90	0.497	171.16	0.00291
TurningBody	16463	Turning	1243.43	16.60	0.451	0.320	64812.34	64.81	560.79	9353.72	1.72	83.41	0.029	19.93	0.00144
											52.21			930.86	0.75966 dBA
Fixed Handle															
FacingFH	1005	Side facing	659.54	16.6	0.590	0.047	34377.81	34.38	389.13	953.30	1.92	79.499	0.032	34.30	0.00093
TurningFHA	2226	Turning	1031.85	16.6	0.614	0.05	53784.36	53.78	633.56	1651.18	1.54	79.894	0.026	32.47	0.00079
TurningFHB	3517	Turning	923.18	16.	0.526	0.046	46380.36	46.38	485.59	1122.22	3.16	79.010	0.053	36.71	0.00144
TaperingFH	258	Tapering	365.209	16	0.579	0.073	18348.10	18.35	211.46	775.52	0.31	79.370	0.005	34.92	0.00014
											6.93			138.40	0.33050 dBA
Moving Handle															
FacingMH	1005	Side facing	540.07	16.60	0.533	0.033	28150.35	28.15	287.85	495.14	3.71	78.359	0.062	40.17	0.00154
TurningMHA	2226	Turning	1272.59	16.50	0.749	0.048	65932.99	65.93	953.17	2370.42	1.00	82.417	0.017	22.89	0.00072
TurningMHB	3517	Turning	1155.62	16.00	0.764	0.043	58058.55	58.06	882.90	1907.34	1.86	82.286	0.031	23.31	0.00133
TaperingMH	258	Tapering	367.66	16.00	0.830	0.05	18471.14	18.47	305.16	766.55	0.30	82.512	0.005	22.59	0.00022
DrillingMH	1529	Drill	189.292	7.50	0.110		4457.83	4.46	20.82	919.43	1.34	68.303	0.022	161.95	0.00014
											8.20			270.91	0.39502 dBA
Fixed Jaw															
MillingFJ1	1905	Side milling	269.37	50	0.190	0.5	42290.31	42.29	51.18	1279.48	1.50	76.581	0.025	51.40	0.00049
MillingFJ2	2483	Side milling	221.30	50	0.219	0.5	34743.47	34.74	48.16	1211.60	2.02	75.879	0.034	56.66	0.00060
MillingFJ3	784	Side milling	265.26	50	0.183	0.491	41645.19	41.65	48.54	1191.70	0.68	76.178	0.011	54.36	0.00020
											4.20			162.42	0.12888 dBA
Moving Jaw															
MillingMJ1	1905	Side milling	579.65	50.00	0.224	0.345	91004.89	91.00	129.84	2239.76	0.08	72.045	0.001	96.40	0.00001
MillingMJ2	2483	Side milling	589.48	50.00	0.248	0.491	92547.58	92.55	146.19	3588.96	0.76	73.124	0.013	83.01	0.00015
MillingMJ3	3815	Side milling	770.82	50.00	0.248	0.484	121019.21	121.02	191.16	4626.17	0.93	74.528	0.016	68.33	0.0002
TurningMJ	5848	Turning	1499.99	7.50	0.599	0.384	35324.98	35.32	898.50	8125.31	0.79	85.583	0.013	14.76	0.00089
											2.56			262.50	0.12837 dBA
TOTALS											74.09			1765.09	1.7424 dBA

3.5.3 Comparison of calculated, and optimised noise results.

For the optimised process parameters, the predicted noise dose was 1.74 dBA, compared to the Anylogic computed noise of 4.76 dBA for the unoptimised processes. The noise levels for the individual operations are shown in Figure 14. This reduction in noise has a production penalty: First round calculation of machining time with Anylogic (Table 6): 39.40 min, with second round optimisation of noise: 74.09 min (Table 7).

This reduction globally occurred for all machining operations. MillingB2 has substantially reduced the noise, followed by these respective operations such as MillingB3, TurningMJ, MillingFJ2, MillingFJ1, FacingFH, MillingFJ3, MillingB1, MillingB4, and TaperingFH. This reduction is possible due to lowering cutting parameters and workpiece structure. Furthermore, DrillingMH, MillingMj1, MillingMJ2 and MillingMJ3 operations show almost unchangeable noise values. While MillingMJ1 has lower noise value for both techniques. It should be noted that in this somewhat simplified analysis, the noise regression is for tapering, drilling and the assumption made here is that the cutting dynamics are similar for milling. The results are therefore more a proof of principle than a definitive statement of noise levels.

Figure 14: Results of calculated and optimised noise. Calculated noise refers to "Anylogic computed noise Cnc/Tnc" in Table 6b and includes both the intensity of the noise and its duration.



3.5.4 Production time and noise exposure for the optimisation process the whole product

For the whole product, the production noise was calculated with the reference time duration of the overall process. This was calculated for total project duration (Sum of task durations) or whole machining of the tap wrench. The optimization noise exposure (C_{no}/T_{no}) was 1.74 dBA for a machining time of 74.09 min (comparable to the 39.40 min for the first simulation). This compares favourably to the 4.76 dBA for the first simulation and shows that noise reduction could be achieved by change in process parameters.

4. Discussion

4.1 Findings

This study has applied a SD simulation approach to improve workshop safety by optimising the machining cutting parameters for noise. Investigation shows that these parameters such as cutting speed, cutting feed rate, and cutting depth have influence on produced machining noise. Material removed, material removed rate and machining time have also involved the analysis. Anylogic architectures and noise production models of Tap wrench have been developed.

The main findings are that it is possible to reduce noise exposure by optimising machining parameters over multiple work stages. The process requires an equation for noise as a function of machining parameters, but once that is established the optimisation process may be undertaken.

However, this noise reduction comes with a large loss of productivity. In the first simulation (Table 6a) the machining time is 39.4 minutes (plus an inferred setup time of 133.08 minutes). In the noise-optimised simulation (Table 7) the machining time is 79.09 minutes (plus the same inferred setup time of 133.08 minutes). Thus, an additional 40min machining time, about a 100% increase. Hence the results are disappointing, and the overall method is not able to achieve the objective of simultaneously optimising both the minimisation of noise exposure and minimisation of machining time.

The main issue addressed by this paper is occupational noise exposure. The current method has approached the problem by seeking to optimise process parameters, i.e. to control the machine settings. This potentially fits well in an industrial engineering setting, where it is common for manufacturing instructions to include the drawings and the machine settings, as determined by the industrial engineers.

In contrast existing noise control methods tend to be directed towards workshop layout (e.g. noisy machines co-located), stiffer machine tools and fixtures, sharper tools (or tools that keep their sharpness longer), acoustic enclosures around the cutting area, use of sound level meters to identify hot spots, and personal protective equipment. The approaches are complementary.

4.2 Implications for practitioners

Implications for industrial engineers

The implications are for industrial engineers who setting up machining processes. In these situations, it common to optimise for takt time, i.e. make the production process more efficient. However, we show that attention to noise can also be included in the optimisation process for the production plant. This has the benefit of giving explicit consideration to health and safety, especially the long-term chronic harm of hearing loss. We are suggesting that noise levels be included in plant optimisation, and we have shown a method whereby this can be achieved.

Application of the findings to health and safety practice

For health and safety practitioners working in industry, to repeat the whole study for each operational task would likely be too onerous. Nonetheless there are some general findings that could be useful. First, the findings show that milling and drilling, are the noisiest tasks. Taking for example the process MillingB2, an interpretive summary is shown in Table 8. It is worthwhile – from the perspective of noise reduction – to slow down the tool both in rotation and forward speed and decrease the depth of engagement. Although this also proportionally increases the time taken to complete the task, the noise exposure is reduced.

Hence H&S practitioners are recommended to pay particular attention to these tasks.

Table 8: Interpretive summary for the process MillingB2, with parameters before and after the optimisation.

Operation	Material removed (mm3)	Machining	Tool & piece rotation (rpm)	Tool & piece Diam (mm)	Cutting Feed Rate & Cutting radial depth (mm/rev)	Cutting axial depth (mm)	Machining time (min)	Computed noise level (dBA)	Noise exposure Cnc/Tnc (dBA/100)
MillingB2 (Before)	9719.00	Side milling	800.00	50.00	0.250	0.50	1.94	98.24	0.01295
MillingB2(After)	9719.00	Side milling	500.00	50.00	0.246	0.164	9.83	67.88	0.00095
Interpretation of the change			Slower rpm	No change to tooling	Forward speed lightly reduced	Tool less deep in the materia l	Machining time increases	Noise is significantl y reduced, but over a longer time	Noise exposure decrease s

4.3 Limitations and opportunities for future research

The major limitation of this work was the inability to simultaneously optimise both the minimisation of noise exposure and minimisation of machining time. This is a difficult problem because the two effects act in opposite directions. Noise is reduced by slowing down the metal removal process, especially the depth of cut (per Figure 2), but this also increases the time taken to complete the machining, thus worsening the productivity. In principle it should be possible to solve this dual optimisation problem: this is part of a broader class of multi-objective optimisation problems. However, a method to achieve this in Anylogic could not robustly be achieved. The solutions for this class of problem are primarily to either blend the two objectives with assigned weights indicating importance, or to select one parameter for optimisation and then run a second optimisation for the other (hierarchical treatment). A possible way forward is to use algorithms (such as *gurobi*) that provide these features.

One of the limitations is that recorded times were only available for the machining operations as a whole. These times included both machining and set-up time, with no differentiation. In practice the set-up times were occasionally as long as – or longer than - the machining times for operations, so it would have been advantageous to record the set-up times separately.

A related time issue is the large difference between simulated times and actual times. This has been attributed to the simulation not accounting for the initial setup times, delays needed after each machining pass, and closure tasks. However, the times were not recorded for these sub tasks. Future studies would benefit from a finer definition of the workflow when measuring times.

It would also be interesting to understand why students took so long with the set-up. To some extent this may be explained by their lack of experience and cautiousness approaching machine tools for the first time. By completing a deeper analysis of the set-up times, it may be possible to identify where students lacked confidence or needed more training. Another research approach could be to use eye tracking to determine what students were looking at, and for how long. It is also possible that virtual reality might be used to help familiarize students with the processes beforehand, hence being more confident and efficient when using the real machines.

Another limitation is that the noise equation is for continuous metal removal. There are some situations whereby a chattering noise can be generated, and this equation does not represent such noise. This situation occurs for example when turning a bar of rectangular cross section, which arises in the turningBody operation.

Also, the noise equation is based on data for turning. Practically, others different equations which are specific for each type of machining process such as milling and drilling were used. In principle this could be done for any type of process, and the method is able to accommodate whatever the resulting equations. Opportunities for future work include the establishment of regression equations for noise as a function of machining parameters for milling and drilling.

Furthermore, the present study only includes machining parameters in the optimization and assumes that the effects are linear (as evident in the use of a linear regression equation). Consequently, the model is only valid for the specific parameters, tooling setup, and workpiece material used in the study. A model would need to be constructed for each new application.

In the present work the frequency characteristics of the noise have been implicitly included in the dBA scale. This weighted scale represents the effect on human hearing and is the standard approach for determining occupational noise dose. A potential future research area could be to examine the level of hazard of particular frequencies, with a view to reduce those.

A possible direction for future research might be for machine tool vendors to provide some of the parameters as part of the specifications of their equipment, so that production engineers could more readily include machining noise in purchasing decisions.

Future research could integrate the noise calculations into plant simulations. To some extent this has been shown in the present paper, but only for a systems dynamics model. There would be advantage in being able to do this with discrete event simulation (DES) or agent-based approaches, as these are more generally used to represent production environments. However, this is not straightforward, as it requires noise algorithms which are not easy to find in the literature. In addition, these algorithms would need to be embodied in the simulation software, and there would need to be a reliable way of solving them. Another idea might be the integration with cost calculation.

5. Conclusions

The objective of this project was to create a functional model of a production process for the purposes of calculating machining time based on metal removal rate, and to optimise the machining parameters for maximal noise reduction. This work shows that this can be achieved by extracting a noise equation from the literature and using it in a systems dynamics model of a production process, to determine and optimise noise. The method was applied to a case study of a tap wrench as manufactured by students as part of their engineering training.

The research approach involved development of a systems dynamics model of the machining process from the perspective of metal removal rate. This represents idealized production times, which are not representative of actual practice, nonetheless such times may be computed in a consistent way. A model for noise as function of process parameters was also included in the simulation, for all of turning, milling and drilling. There is a lack of such models in the literature. The regression equations were then used as the optimization function, to change process parameters to minimize noise, while also seeking to preserve total production time (hence also productivity). The outcomes show that it is indeed feasible to implement such process improvements for noise, however the dual optimisation of productivity remains elusive.

The originality of this work is describing a method whereby results from a noise study on a process may be used to create a regression equation for noise as a function of multiple process parameters. This can then be included in a simulation, to calculate occupational noise exposure dose for the multiple machining tasks that make up a realistic production sequence. The benefit of using a regression approach is that it allows a quantification of the complex dependency between noise and process parameters, which is not obvious due to the number of parameters and their interactions.

The benefit of constructing a simulation model is that it provides the tools to optimise noise exposure: i.e. change machine process parameters to reduce noise. This is challenging to do because generally cutting slower or making less deep cuts will reduce noise, but at the cost of worsening the productivity metrics. Implications for safety practitioners are that this work shows a methodology whereby small changes in process parameters, that would not be apparent by causal inspection, may be made to reduce noise.

Conflict of interests

The authors declare no conflict of interest.

Contribution statement

Conceptualization: G.M.T, DP; Data curation G.M.T; Formal analysis G.M.T; Investigation G.M.T; Methodology G.M.T; Software G.M.T; Resources D.P; Supervision D.P, G.S, Y.Z; Validation G.M.T; Visualization G.M.T; Writing – original draft G.M.T; Writing – review & editing G.M.T, D.P, G.S, Y.Z

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Appendix A: Raw noise data

Noise level (dBA) was measured for the following machining operations: milling and drilling. Both operations were on mild steel, using the same machine as used for the tap wrench. Drilling was conducted with the milling machine. The milling process used no lubricant, drilling used a water borne emulsion cutting fluid.

Algorithms were determined from experiments conducted in the workshop. A design of experiment (DoE) approach was taken to determine combinations of process parameters.

Noise was measured using a “Professional Sound Level Meter” (QM1598) in a workshop with hard reflective surfaces, at a distance of 470 mm from the machine during the machining operations. The accuracy class of the noise meter was ± 0.01 dBA. One repetition of noise measurement was performed for each machining operation.

A.1 Milling data

The milling machine was a turret vertical type (KING RICH Industries Co., model KR-V3000SL), using an end-mill cutter diameter 50 mm with 5 carbide tips (model Viper Bit manufactured by Sutton Tools Industry). Substrate was mild steel plate x: 200mm length x y: 35mm breadth x z: 16.6mm depth. The milling process was facing milling.

Run order	Cutting Speed (m/min)	Cutting Axial Depth (mm)	Cutting Feed/Tooth (mm)	Cutting Feed (mm/min)	Tool Diameter (mm)	Measured noise (dBA)
1	78.5	0.1	0.1	125	50	71
2	125.6	0.1	0.1	125	50	74.3
3	172.7	0.1	0.1	125	50	73.1
4	78.5	0.3	0.1	125	50	72.5
5	125.6	0.3	0.1	125	50	75.2
6	172.7	0.3	0.1	125	50	81.2
7	78.5	0.5	0.1	125	50	73.3
8	125.6	0.5	0.1	125	50	78
9	172.7	0.5	0.1	125	50	85.1
10	78.5	0.1	0.25	200	50	76.5
11	125.6	0.1	0.25	200	50	75.2
12	172.7	0.1	0.25	200	50	76.4
13	78.5	0.3	0.25	200	50	74.5
14	125.6	0.3	0.25	200	50	78.8
15	172.7	0.3	0.25	200	50	89.6
16	78.5	0.5	0.25	200	50	74.8
17	125.6	0.5	0.25	200	50	95.8
18	172.7	0.5	0.25	200	50	98.3
19	78.5	0.1	0.5	275	50	73.7
20	125.6	0.1	0.5	275	50	75.1
21	172.7	0.1	0.5	275	50	77.4
22	78.5	0.3	0.5	275	50	74.2
23	125.6	0.3	0.5	275	50	87.2
24	172.7	0.3	0.5	275	50	91.5
25	78.5	0.5	0.5	275	50	77.4
26	125.6	0.5	0.5	275	50	97.3
27	172.7	0.5	0.5	275	50	102.7

A.2 Drilling Data

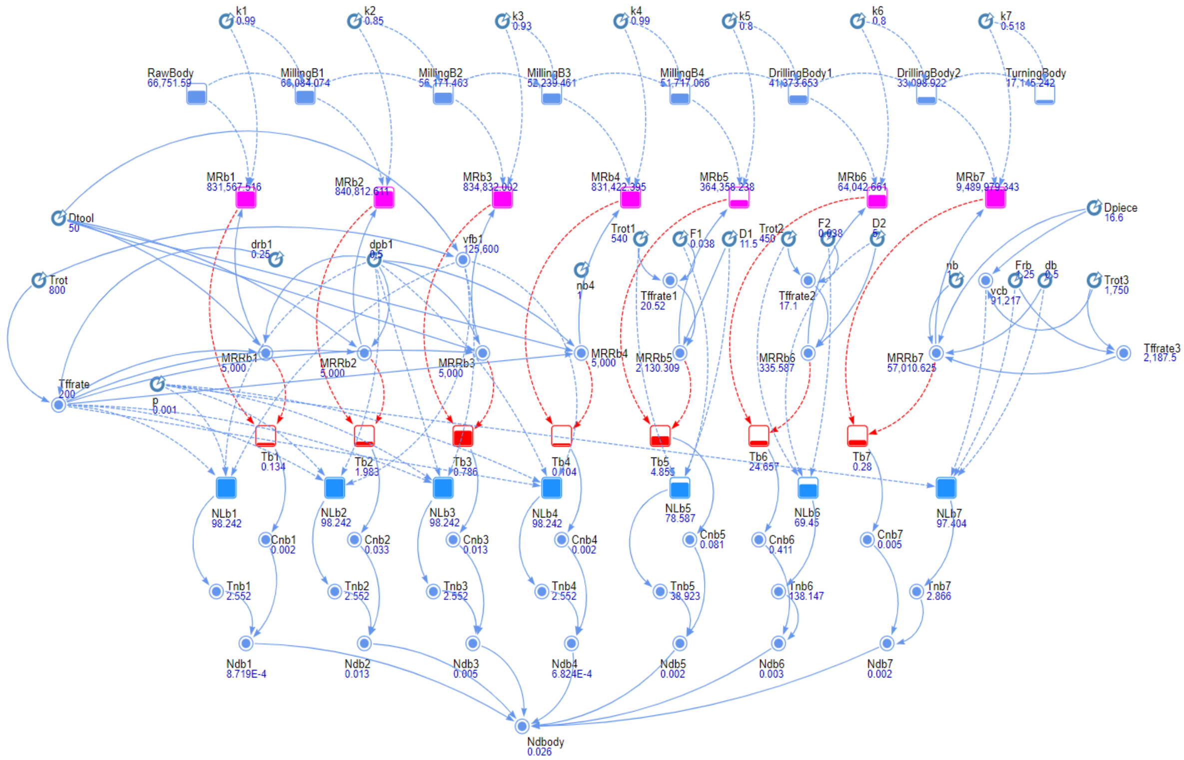
Drill bits were jobber Drill Blue 5 mm and Jobber Drill Black Jet 11.50mm, high speed steel from the same manufacturer as for end-mill cutters.

Run order	Cutting Speed (rpm)	Cutting Feed Rate(mm/rev)	Diameter Tool (mm)	Measured Noise (dBA)
1	540	0.038	11.5	78.5
2	540	0.076	5	63.8
3	540	0.152	5	68.3
4	350	0.038	7.5	71.2
5	200	0.076	5	66.3
6	350	0.038	5	70.2
7	200	0.038	5	64.2
8	200	0.152	11.5	75.6
9	540	0.038	7.5	74.5
10	350	0.076	5	70.1
11	540	0.038	5	73.8
12	350	0.076	11.5	75.8
13	350	0.152	7.5	73
14	200	0.038	11.5	69.8
15	200	0.152	5	65.1
16	540	0.076	11.5	79.1
17	200	0.038	7.5	64
18	540	0.076	7.5	76.2
19	350	0.152	11.5	77.8
20	540	0.152	7.5	80.1
21	200	0.076	7.5	64.8
22	350	0.076	7.5	74.5
23	350	0.152	5	75.6
24	200	0.152	7.5	67.5
25	350	0.038	11.5	73.7
26	200	0.076	11.5	72.3
27	540	0.152	11.5	80.5

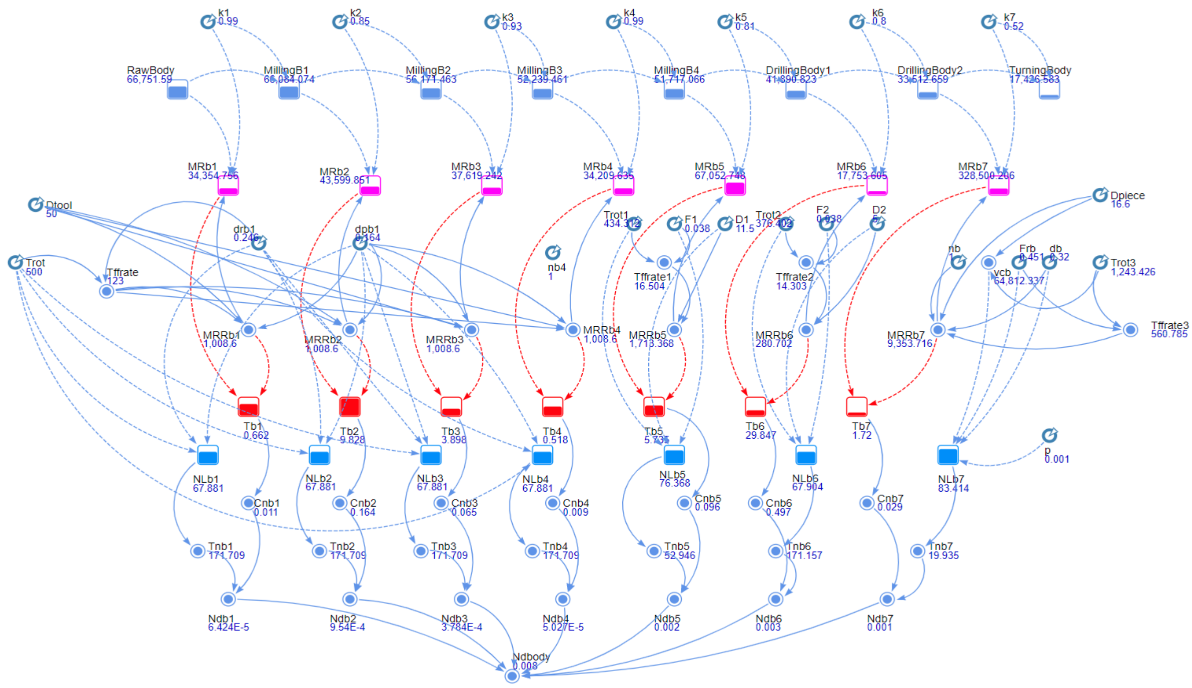
Appendix B: Model details

B.1: Machining of Body of Tap Wrench

Overall Values

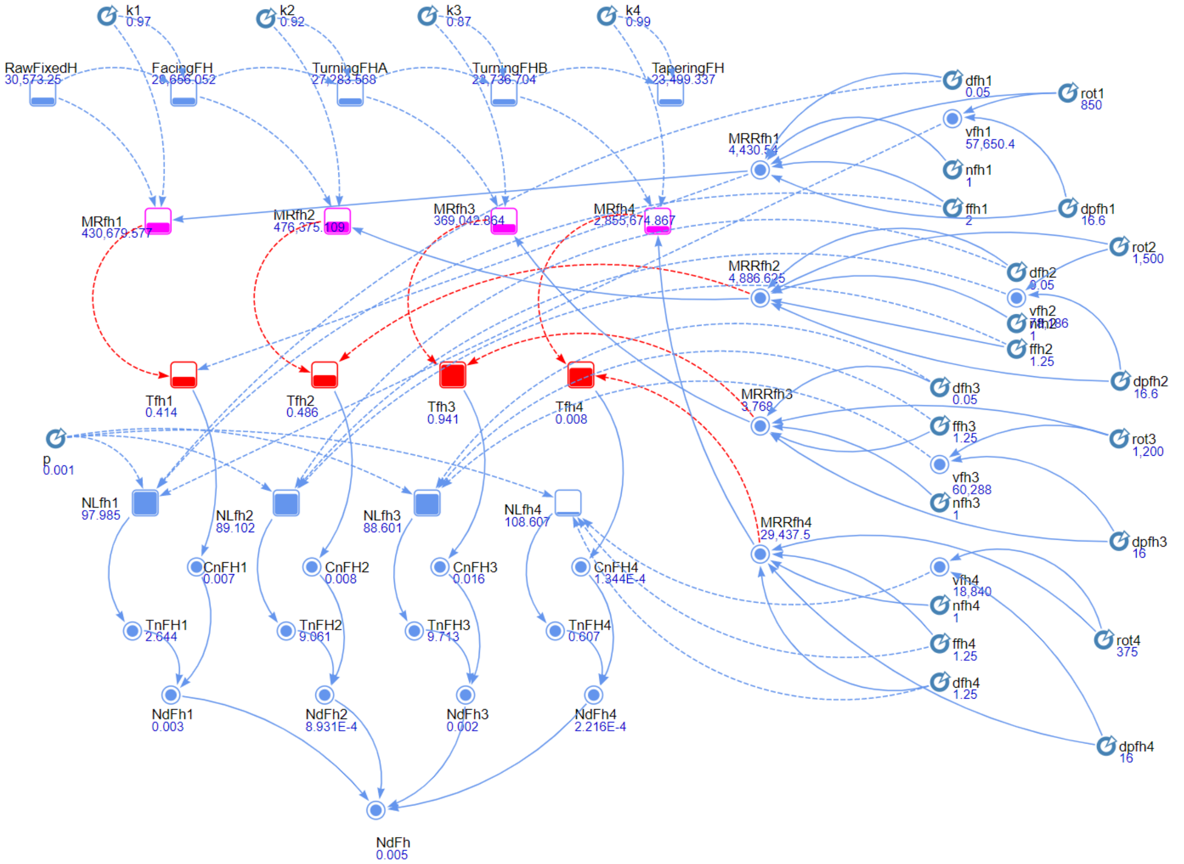


Values with optimised parameters

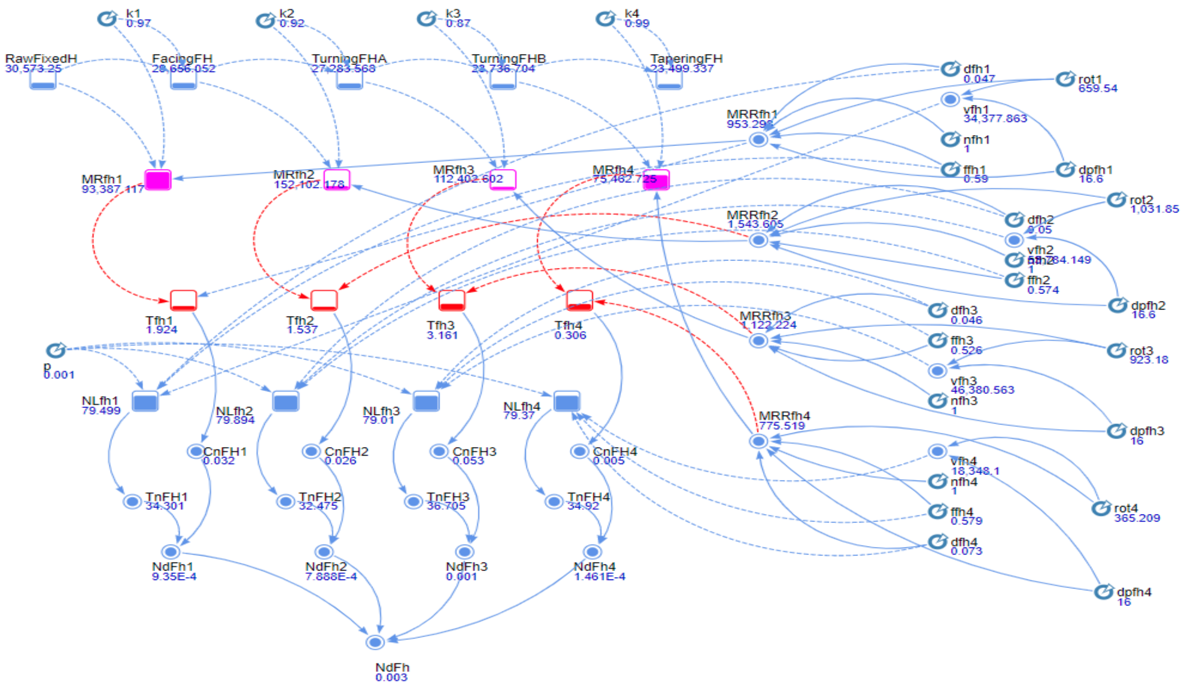


B.2: Machining of fixed handle of Tap Wrench

Overall Values

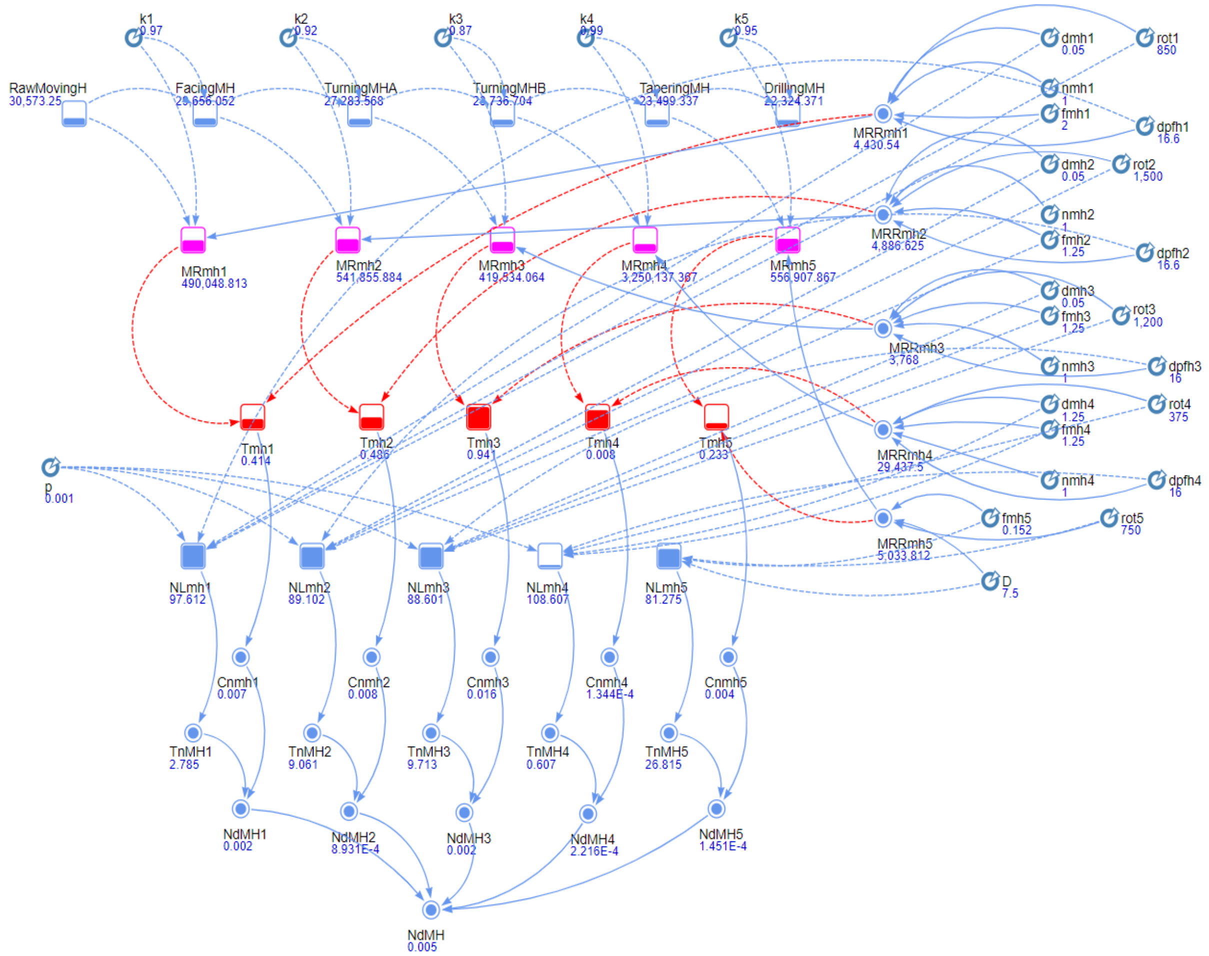


Values with optimised parameters

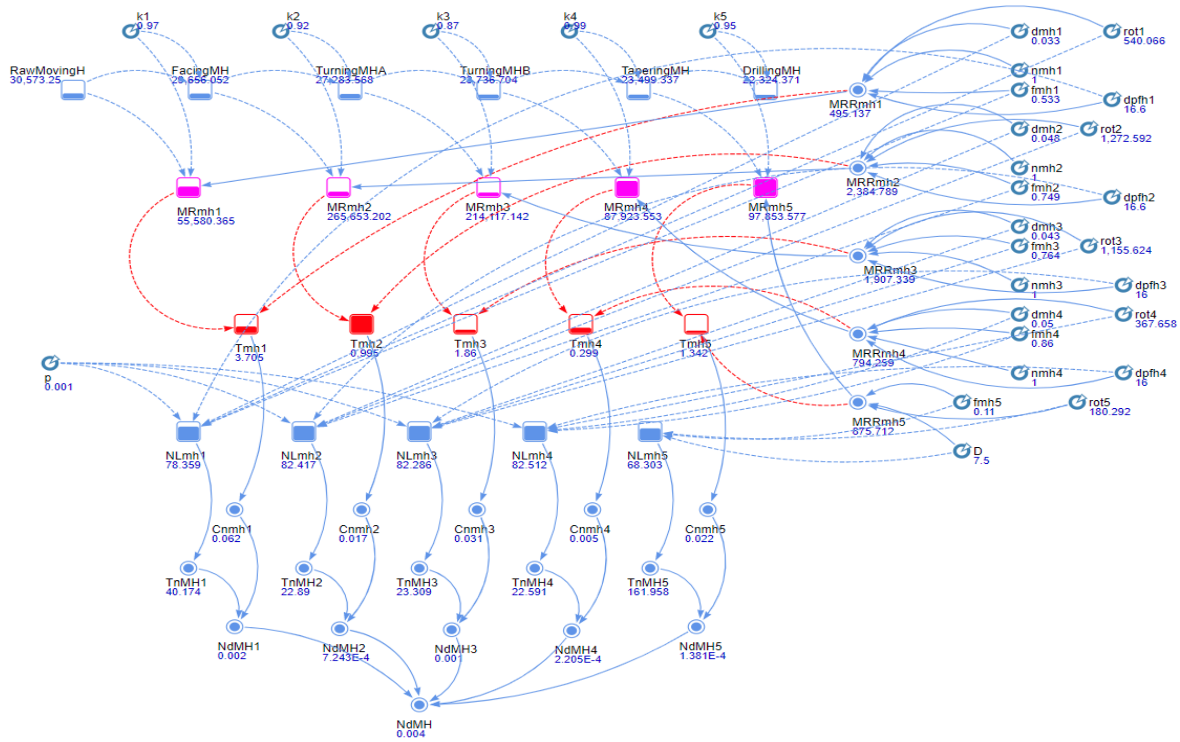


B.3: Machining of Moving handle of Tap Wrench

Overall Values

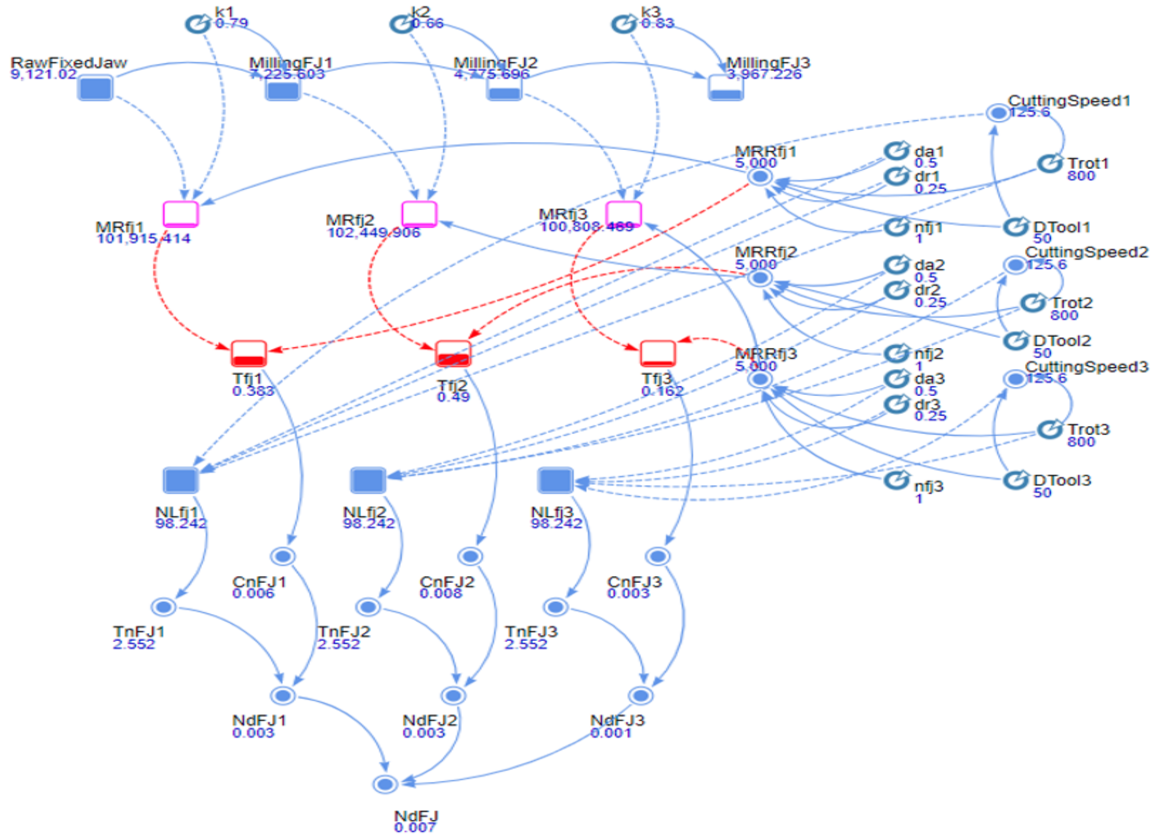


Values with optimised parameters

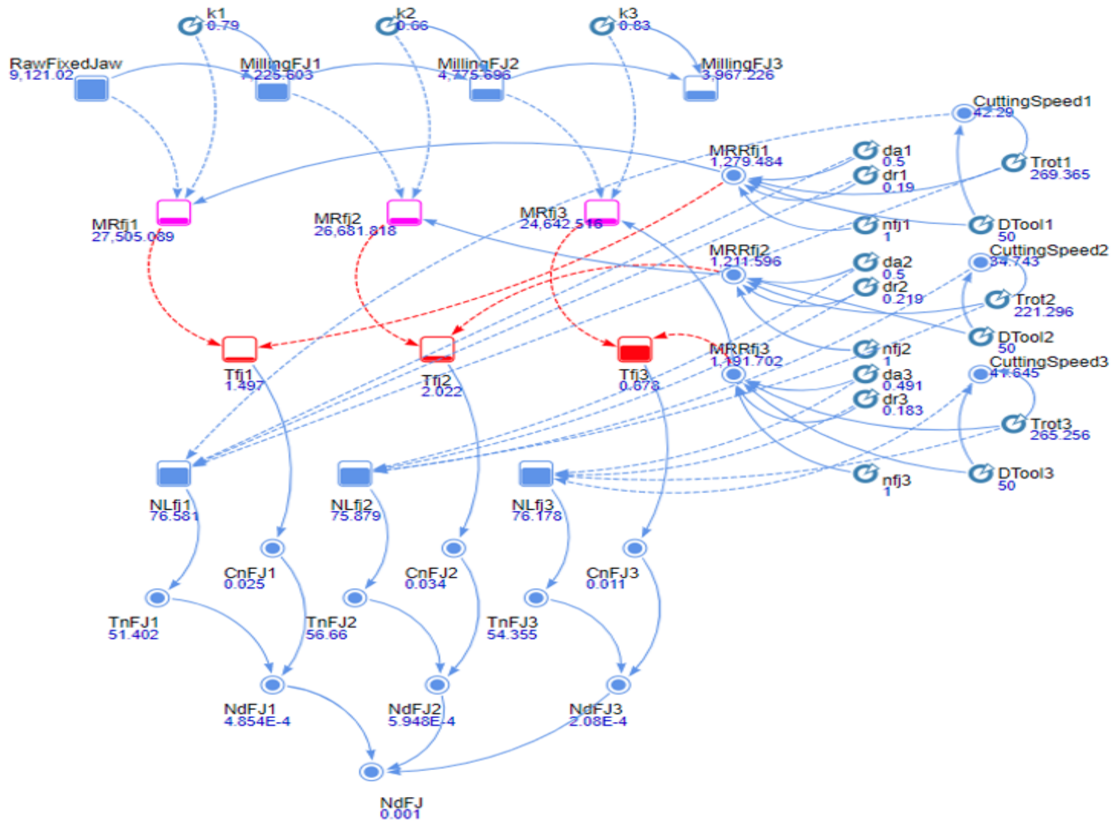


B.4: Machining of Fixed Jaw of Tap Wrench

Overall Values

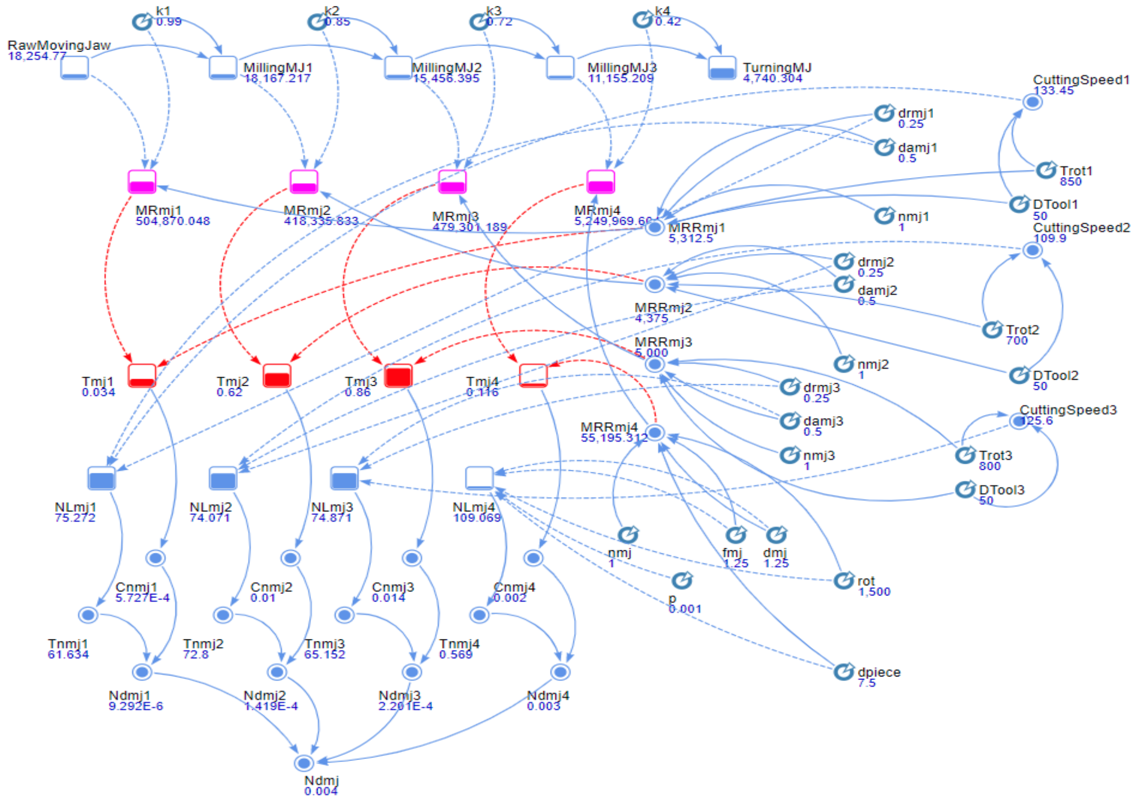


Values with optimised parameters

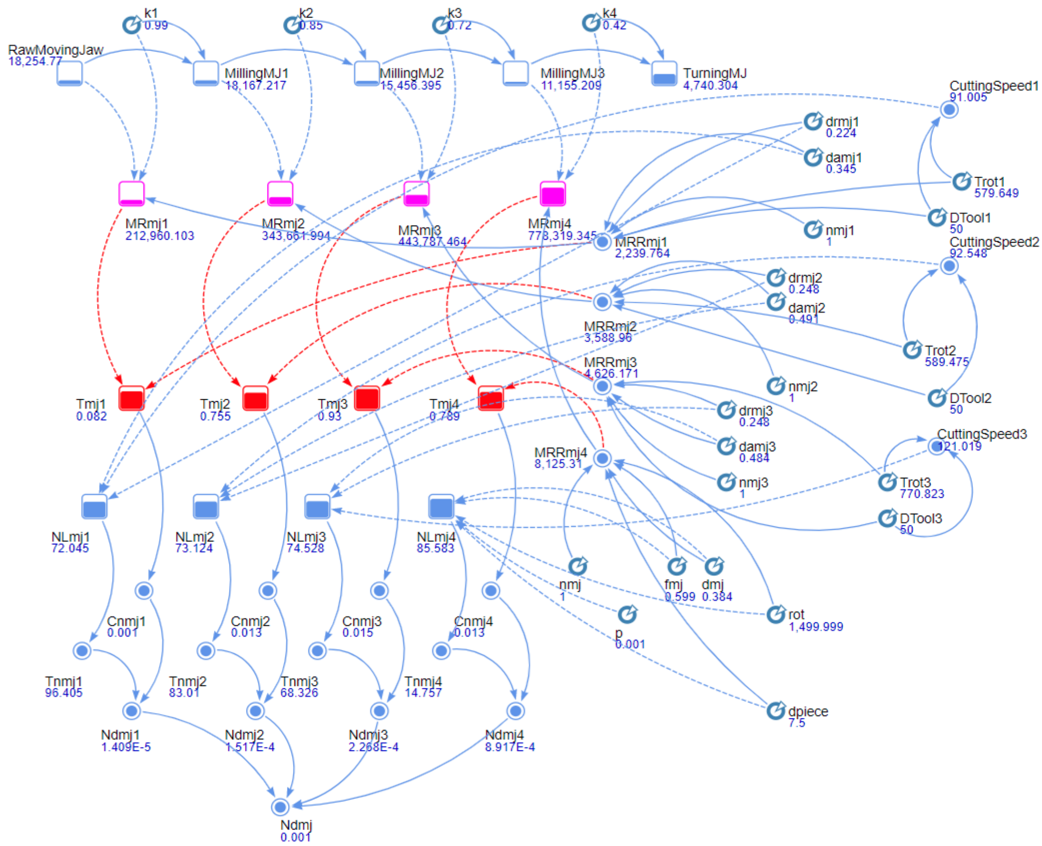


B.5: Machining of moving Jaw of Tap Wrench

Overall Values

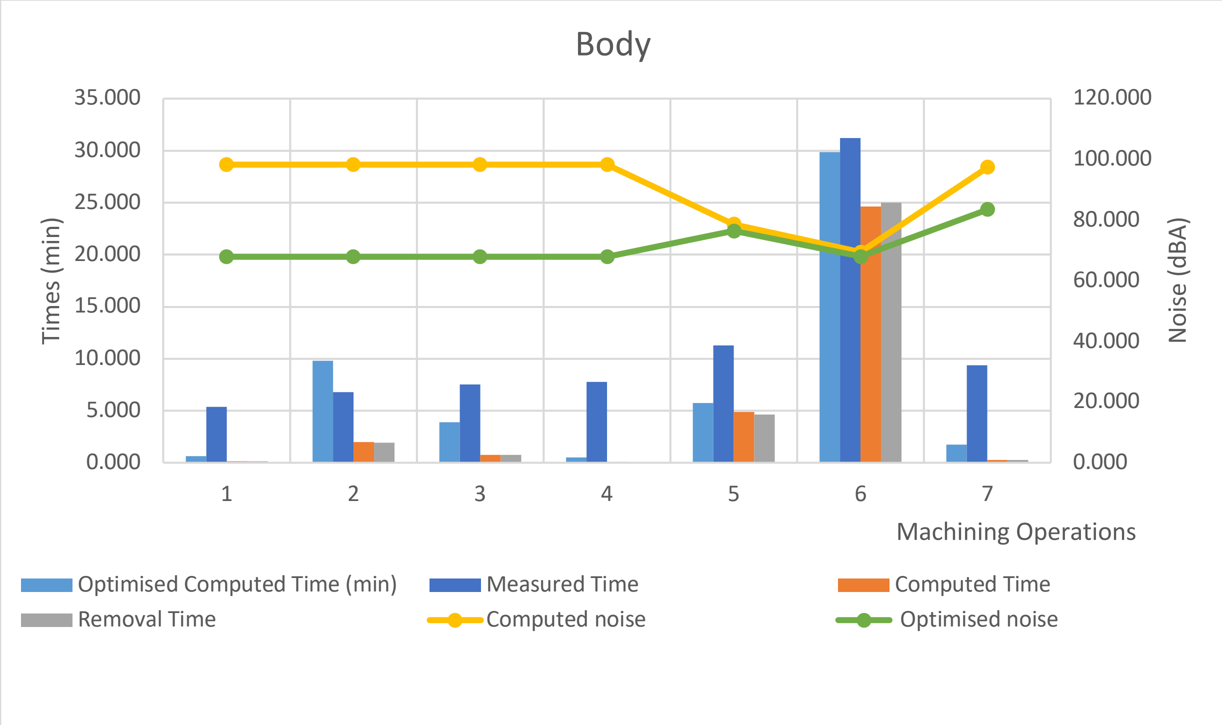


Values with optimised parameters

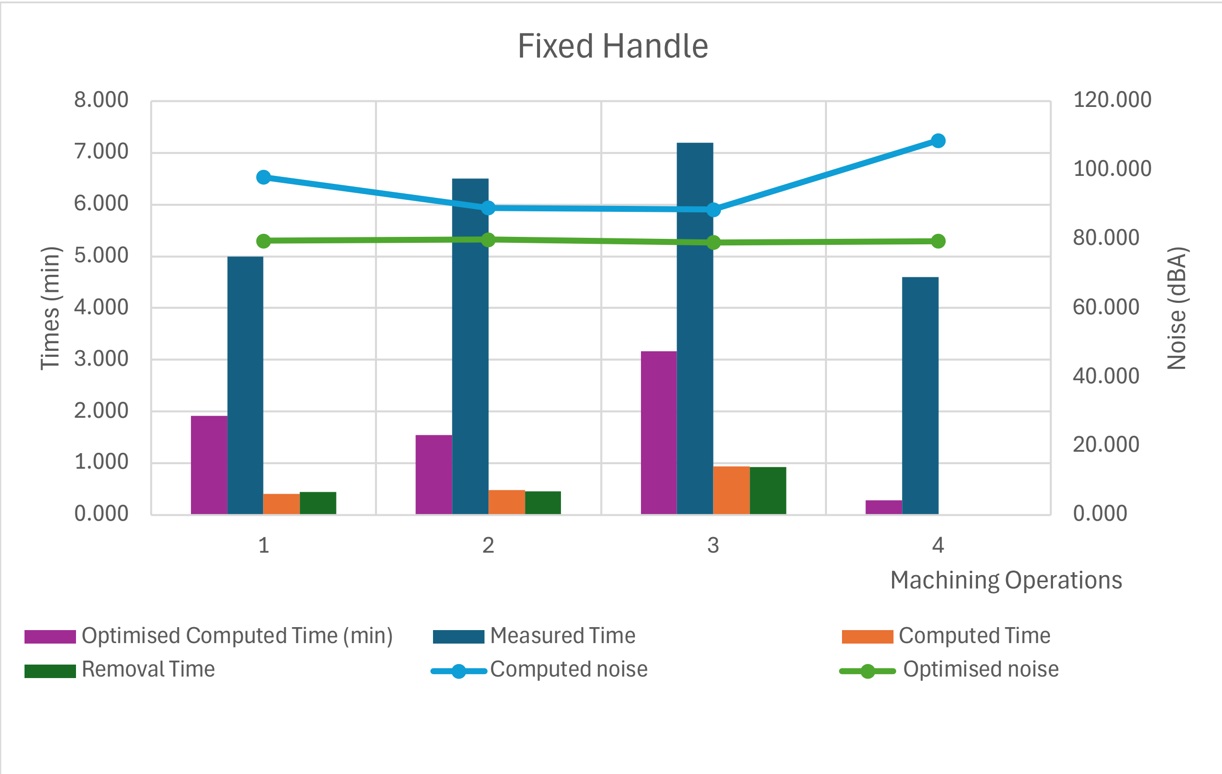


Appendix C: Detailed noise level and times results

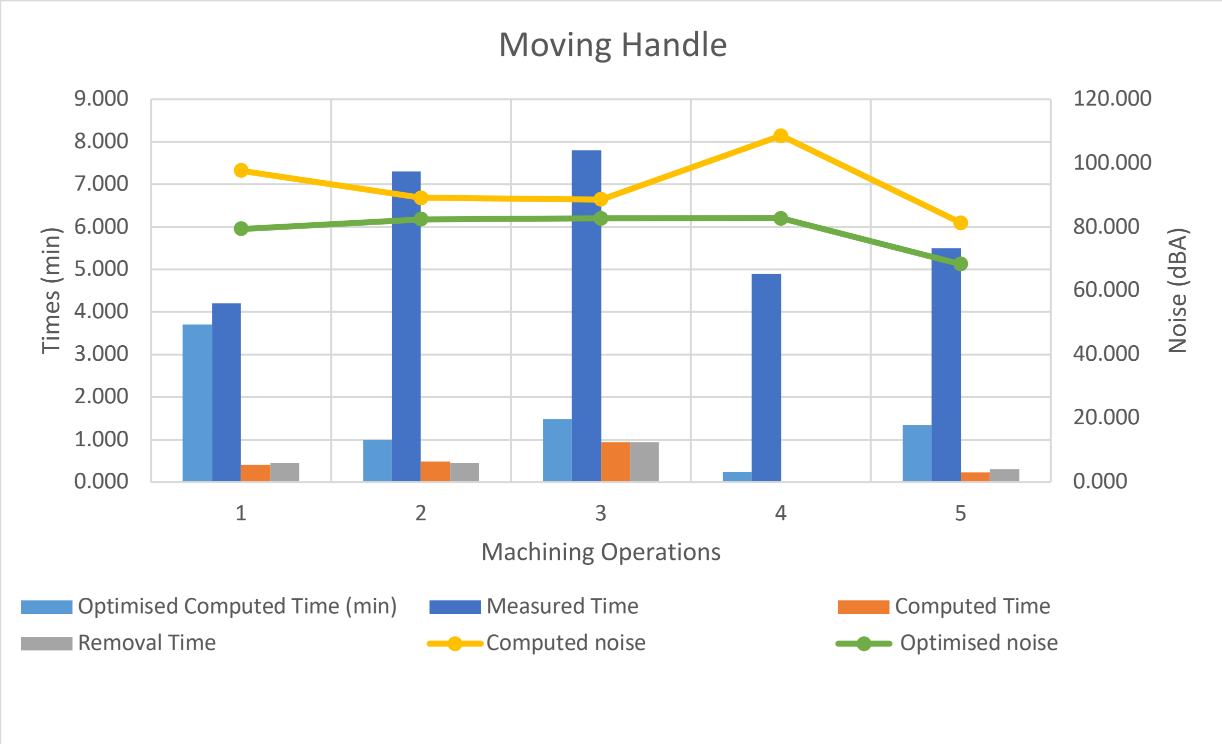
C.1: Default machining values of body noise level and times result which were obtained throughout seven machining operations.



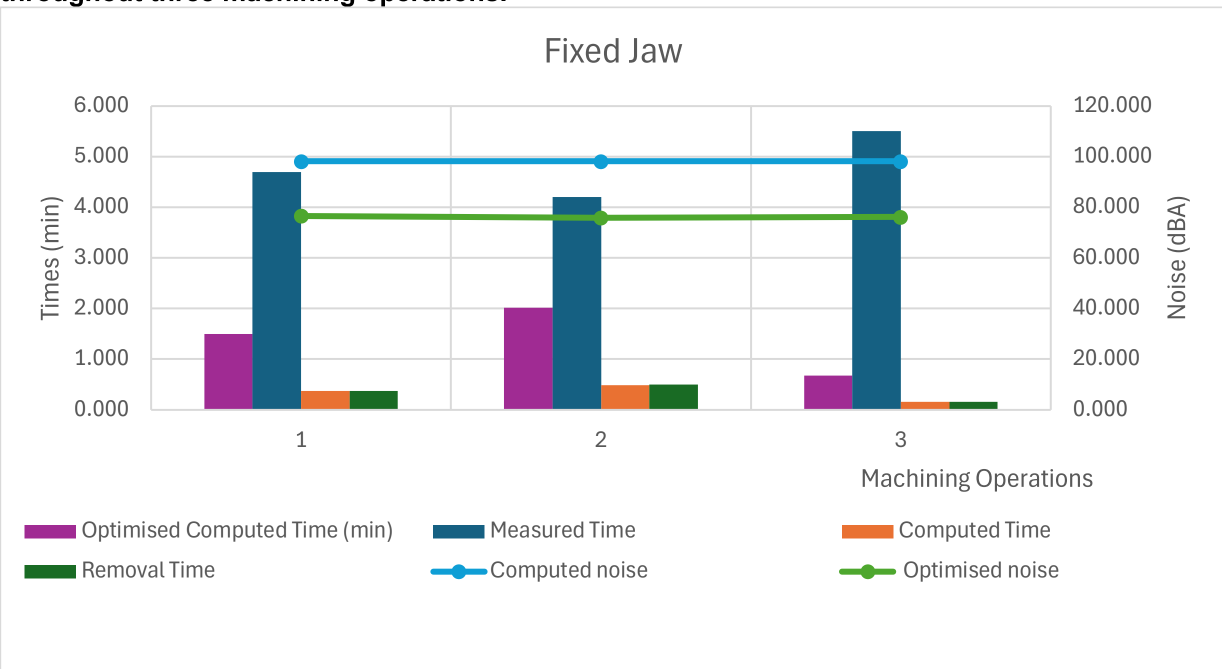
C.2: Default machining values of fixed handle noise level and times which were obtained throughout four machining operations.



C.3: Default machining values of moving handle noise level and times which were obtained throughout five machining operations.



C.4: Default machining values of fixed Jaw noise and times results which were obtained throughout three machining operations.



C.5: Default machining values of Moving Jaw time results which were obtained throughout four machining operations.