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Cutting-insert selection and cutting-parameter optimization for turning operations based on artificial neural networks and genetic algorithm

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Abstract

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The objective of the present research is to obtain an expert system for optimal cutting-insert selection and cutting parameter optimization. The proposed approach addresses turning processes that use technical information from a tool supplier. The proposed expert system is based on artificial neural networks and a genetic algorithm, which define the modeling and optimization stages, respectively. For the modeling stage, two artificial neural networks are implemented that evaluate the feed rate and cutting velocity parameters. These models are defined as functions of the insert features and working conditions previously defined. For the optimization problem, a genetic algorithm is implemented to search an optimal tool insert. This heuristic algorithm is evaluated using a custom objective function that qualifies the performance of the machining on the basis of given working specifications, for instance, the lowest power consumption, the shortest machining time, or an acceptable surface roughness.

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Thesis organization

This thesis contains six chapters, organized as followed:

1. Chapter 1: Introduction. This chapter introduces the general issues around turning operations, as well as shows some researches related to optimization cutting parameters and cutting performance modeling addresses to metal cutting machining.
2. Chapter 2: Database. This chapter aims to introduce the main features which define a tool-insert. It also introduces the relations between the cutting parameter to the geometrical features, as well as to the working conditions. This chapter defines the database based on commercial data from a tool supplier. The chapter ends with the proposed dataset for this research.
3. Chapter 3: Artificial neural network models. This chapter aims to explain the procedure to obtain the neural network models for this research. Furthermore, the data preparation and error validation are topics introduced by this chapter.
4. Chapter 4: Genetic algorithm optimization. This chapter aims to explain the mechanism behind for genetic algorithm implementation. Some concepts like, chromosome individual, decode and encode procedure, fitness function are introduced in this chapter.
5. Chapter 5: Design Examples. This chapter aims to explain in a detailed manner how to use this model for practical applications. Three examples are shown in this chapter: light roughing machining, heavy roughing machining and finishing operations.
6. Chapter 6: Conclusions.

Chapter 1 Introduction

1.1. Background and general definitions

Nowadays, the manufacturing industry demands technologies which are able to deal with changing environments and customized products. Industry 4.0 and challenging trade by the globalization push companies to be more competitive in both large and small batches. That represents new issues for CNC manufacturing industry which bases its profits in large series productions [1].

During the last few decades, there has been significant progress in CNC machining to improve its efficacy to world challenges. These breakthroughs come from automation approaches, such as adaptive control, active control, etc., which allow to achieved higher operation performances [1]; manufacturing process, for instance Computer Aided Process Planning (CAPP), expert processes planning systems (PP), Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) based on iMachining, etc. [2, 3], which allow both simulate and evaluate variable environments; and complex cutting models which predict fundamental variables related to machining operation performed in industry [4]. These approaches mainly aim to get suitable cutting parameters and control them within certain working conditions, increase the efficiency during the machining process, and reduce the time implementation.

On the other hand, the cutting parameters for machining processes have a high impact on the performance and they are usually the variables to be tuned for optimizing models. Generally, the cutting parameters are cutting velocity, feed rate, depth of cut, cutting forces, torque, spindle speed etc. Moreover, the parameters to evaluate the machining results are usually surfaces roughness, power consumption, machining time, production cost, tool life, production rate etc. [5-7].

For machining process, an accuracy performance can be defined only into a working optimal range. This optimal range is evaluated by models which generally relate working conditions to cutting parameters and tool features. These models can be numeric, analytic, empiric, hybrid or Ai-based models [4]. Nowadays, there is a trend in the use Ai-based models which clearly show an adaptability behavior and high performance in machining operations.

Furthermore, the advances in computer sciences have made possible the widely application of these models in the manufacturing industry. [8-10].

Usually, the implementation stage for machining processes takes much time and sometimes requires previous machining tests to reach acceptable results. On this basis, some approaches seek out to embed knowledge and technical data in machining processes, thus, obtain expert systems which are able to deal with changing conditions in optimal ways and shorter settings times. Many of these expert systems use information coming from CAD models, database, statement rules, tool preferences, suppliers etc. [2-4, 11, 12].

1.2. Related works

Some approaches were considered as a relevant information for the hereto. Those researches are described as following:

In [3] is presented an automatic-optimized tool selector model based on CAD information to infer milling process stages. This approach uses a database from a supplier tools to build an expert system which is able to propose suitable tools and suggest an optimal milling operation planning.

A model to predict the life of a cutting tool base on support vector machine is described in [13]. This approach uses experimental testing to get a nonlinear regression model to estimate and predict the level of wear in a cutting tool. Several sensor are installed around the machine to catch information during the machining and create a database to infer the model.

Some significant remarks were taken from [14] where is detailed the effects of cutting edges preparation geometry in surface hardness, moreover, it is presents how the cutting conditions are related on surface roughness for turning processes. On the same subject, In [4] is detailed several models for chip formation, predicting cutting forces, temperatures, stress, strain based on insert geometries and cutting parameters.

The approach [12] poses a system software to optimized cutting parameters based in genetic algorithms. This model defined objective function based on theoretical models to relate fundamental variables in machining operation.

In [5], an optimization of cutting parameters for turning process is shown. This research defines the surface roughness as an objective function for turning machining of EN 8 STEEL. Furthermore, a genetic algorithm is also applied for this approach. This model can be consider as a hybrid model.

Even though [9] is a research to predict annual power load consumption, this approach also shows an interesting hybrid model based on regression neural networks and fruit fly optimization algorithm. This research presents a significant improvement in accuracy compared with previous approaches without neural network algorithms.

Other models also show important achievements applying train-based models in which neural network algorithm are used, for instance [15] for weld bead geometry prediction; [16] for predicting the tensile behavior of tailor weld blanks; [17] where it is presented a model for surface roughness and tool wear for turning operations; In [18] an artificial neural network is created for prediction of the titanium alloys mechanical properties as a function of alloy composition.

The research [19] poses a singular model for an intelligent stock trading decision support systems. This model capture the stock expert's knowledge by a genetic-algorithm-based fuzzy neural network model.

Other important achievements for cutting parameters optimization there have been proposed using only genetic algorithms. Even though, these approaches show dependency to the working conditions, piece of works and tools, it is clear theses model have a high efficiency to reach optimal result. In [20] a multi-objective optimization of cutting parameters for turning operation is presented. This approach poses an objective function based on power consumption, cutting forces and surface roughness. It is also presented a qualification of chromosomes population, inherent to genetic algorithms, based on feasible individuals. In [21] is presented an approach for cutting parameters for turning operation as well; it is also shown an experiment test for validate the model.

In [22] a model to predict surface roughness is proposed. This model use Response Surface Methodology and genetic algorithm to converge an optimal solution.

[23] shows an approach for cutting parameters optimization using Taguchi method and ANOVA analysis over a database obtained by testing surveys. [24] presents a similar approach using Taguchi method and ANOVA analysis but for optimized surface roughness.

1.3. Research objective

The objective of the present research is to obtain a model for cutting inserts selection and cutting parameter optimization. This model must be constrained by working conditions and evaluated by an objective function. The objective function of this approach is defined by the lowest power consumption, the shortest machining time and a surface roughness into a certain range, nevertheless, this function must be able to be customized under external conditions. Furthermore, the cutting insert selection must be based on commercially available tools.

1.4. Proposed approach

This research poses a model for cutting inserts selection based on commercially available tools, for that reason, it requires a database from a tool supplier. The chosen tool supplier was Sandvik Coromant, the selected tool-insert model to build the datasets was CoroTurn® 107. The information about the recommended cutting parameters and insert feature description was taken from the official Sandvik Coromant website. It is important to emphasize, the taken information from Sandvik Coromant is for academic purposes only.

The planned models for this approach are two artificial neural networks. The first neural network model defines the cutting parameter feed rate as a function of macro-geometrical features and recommended depths of cut. The second model defines cutting speed as a function of material cutting specifications, working conditions, and feed rate cutting parameter.

In order to find optimal cutting parameters and a suitable cutting insert, based on working conditions, a genetic algorithm optimization is proposed. This algorithm is defined by a heuristic search of insert-features and cutting parameters, which are evaluated by the neural network models. This heuristic search is set up under a defined objective function, i.e. the lowest power consumption, the shortest machining time, an acceptable surface roughness.

Given by the heuristic search for the genetic algorithm, the result is a non-existent tool-insert. Thus, the last stage for this approach is to evaluate an Euclidean distance to find the closest existent tool-insert in the commercial database based on predefined threshold distance. That existent insert represents the feasible tool-insert for the model as well with its cutting parameters.

Chapter 2 Database

This chapter aims to introduce the insert features and their correlations to cutting parameters, detail the suggested specifications given by the tool supplier, and show some assumptions which define the final dataset for this research. Finally, this chapter ends with the final datasets which are used to train and validate the neural network models later.

2.1. Introduction to cutting insert features

Turning is a material removal process mainly oriented to metal machining. On this field, several criterial establish the performance for an acceptable turning process, for instance, surface roughness, measurement tolerance, power consumption, machining time, forces, loads etc. These measurement criterial are highly related to the selected cutting insert, cutting parameters, working material, and working conditions [25, 26].

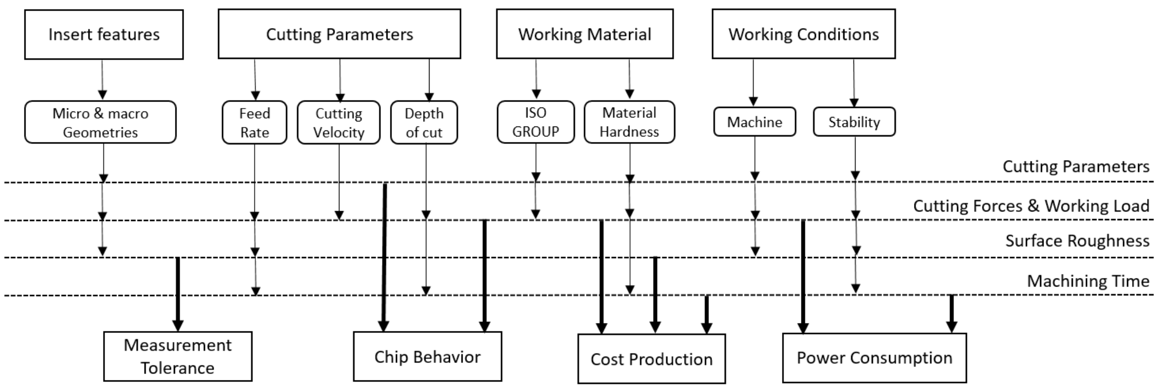

Figure 2.1 Flow chart illustrating the general relationship in the turning process

A cutting inserts vary according to its geometry, shape and material composition, thus, it is possible to apply a specific group of cutting inserts to a specific turning application, working material, and working conditions. Generally, a tool-insert can be defined by its geometrical features and material composition, hereinafter referred as tool-insert features. The most notable tool-insert features are the entering angle or lead angle (KAPR), inscribed circle (IC), clearance angle (AN), cutting edge (LE), corner radius (RE), thickness (S), shape (SC), grade, etc. [27].

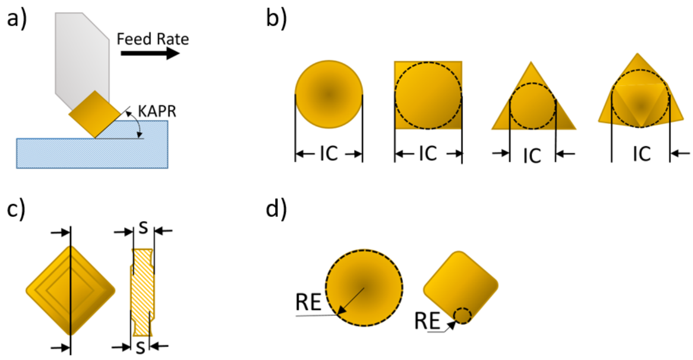

Figure 2.2 Tool-insert features; a) Entering angle KAPR, b) Inscribed circle IC, c) Thickness S, d) Corner radius RE

According to the insert geometry, it is possible to define micro and macro geometries. Micro-geometry features refer to precise geometries targeted to both chip breaking and chip evacuation [4, 25]. Rather, macro geometries determine the general shape of a cutting insert. The macro-geometry features are also related to cutting parameters, machining profile, and accessibility needs. [26, 27].

The inscribed circle (IC) is a tool-insert features highly related to insert size. A large insert size increases the stability performances but an oversizing can lead high production cost. This feature must be linked with the depth of cut, entering angle, and cutting length to be used.

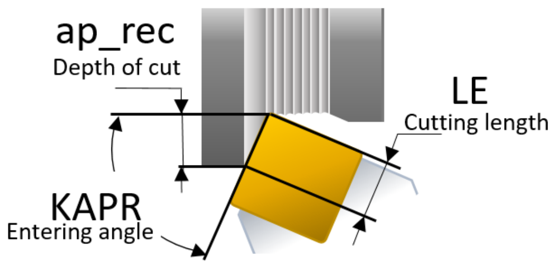

Figure 2.3 Entering angle, depth of cut & cutting length features

The entering angle (KAPR) is the angle between the cutting edge and the feed rate direction in the machining. This feature defines the chip formation, cutting forces direction and cutting edge length in cut. For large values of entering angle, cutting forces are directed toward the chuck which reduces the tendency for vibrations issues. As well, it allows machining shoulders. For small values of entering angle, thinner chip are produced which allows higher feed rates, furthermore, on the cutting edge less load is applied thus the tool life and wear issues can be faced. On the other hand, small values of KAPR cannot turn a 90° shoulders. Finally, entering angle is also related to the tool-holder and accessibility needs. [27]

The clearance angle is the angle between the front face of the insert and the vertical axis of the workpiece [26]. The clearance angle feature also defines the negative or positive quality for an insert. A negative insert has an angle of 90° (0° of clearance angle), while a positive insert has an angle less than 90° (for example 5°, 7°, etc. clearance angle) [27]. The Figure 2.4 illustrates the Clearance angle feature for a tool-insert.

Figure 2.4 Clearance angle feature

On the other hand, nose radius feature (RE) is also related to chip breaking and cutting forces but it is mainly linked to finish surfaces. For a set feed rate cutting parameter, the machining yield a certain surface roughness. Furthermore, radial forces, that push away the insert in the turning machining, become axial forces as the depth of cut increases regarding the radius nose. As a supplier suggestion, the depth of cut should be greater or equal to $^2/_3$ of the nose radius of the tool-insert [26].

The insert shape feature (SC) is the most tangible features mainly selected by accessibility requirements. This feature defines a tool-holder and the depths of cut range in the process. Furthermore, the insert shape feature is defined by the nose angle of the tool-insert, which is related to strength and reliability issues. Large nose angles are stronger, but require more machine power and also increase vibration tendency. Rather, small nose angles are weaker and have small cutting edges but are linked to better surface roughness. [27]

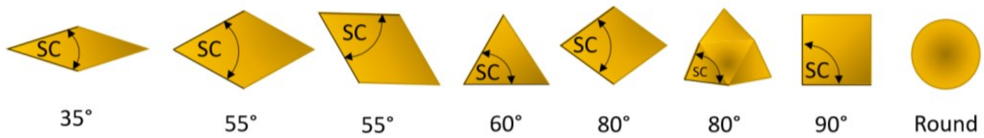

Figure 2.5 Insert shape feature

The Grade of an insert is the feature which describes its material composition. It is selected regarding the workpiece material and working conditions to be used. For a specific grade, there is a range of workpiece material and coating-substrate composition defined. Furthermore, the insert geometry and insert grade complement each other when being applied; for instance, the toughness of a grade can compensate for lack of strength in an insert geometry. Finally, the machine conditions can be set up like, excellent, good, and poor regarding an field of application [27].

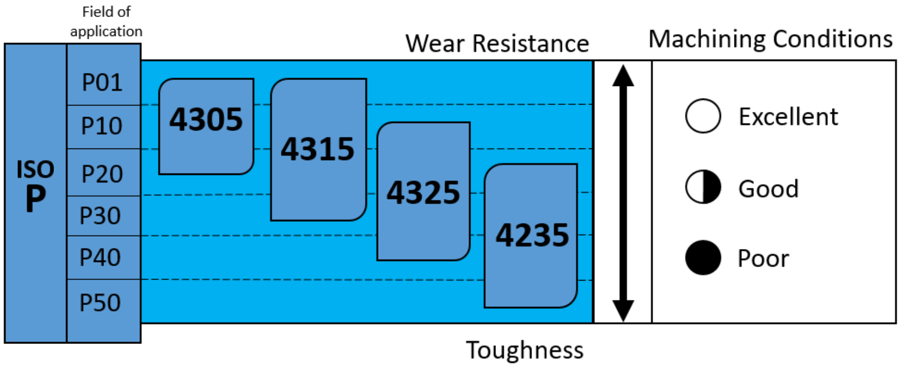

Figure 2.6 Insert grade feature

The field of an application defines the spectrum of possible issues for a turning process, hereinafter referred as area applications. These applications are categorized by six groups which define a certain behavior to both wear resistance and toughness application. The Figure 2.7 describes in detail each ISO area application regarding the ISO P group material.

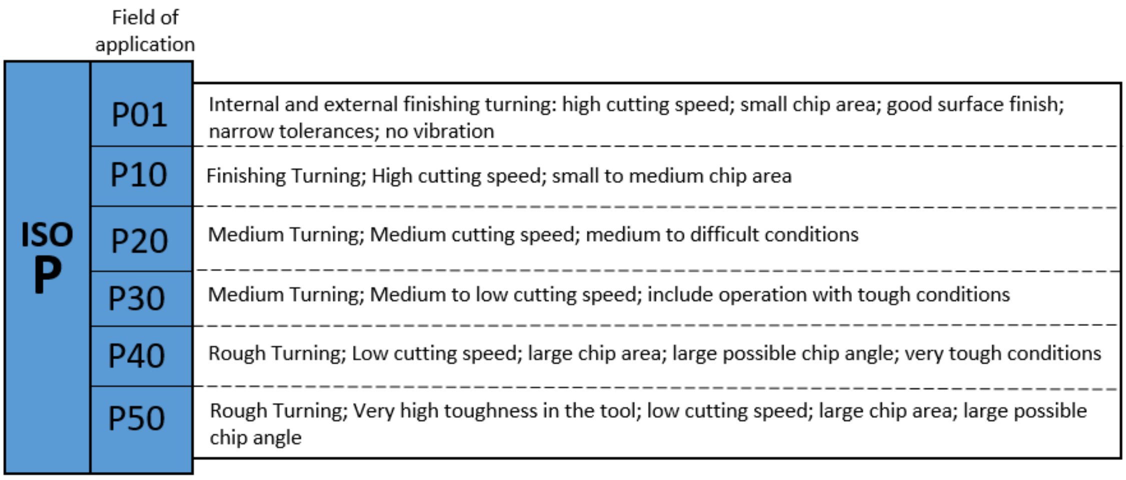

Figure 2.7 Description of ISO-P area application

The workpieces material for metal cutting industry is the main characteristic which influences the selection of a tool-insert. The materials are varied and depend on the alloying elements, iron contend, thermal treatments, hardness etc. The workpiece materials have been divided into six major groups in accordance with the ISO-standard [27]. For each ISO group, there are specific features relate to chip behavior, cutting forces and tool wear issues. The Figure 2.8 shows these ISO groups and the working materials for them defined.

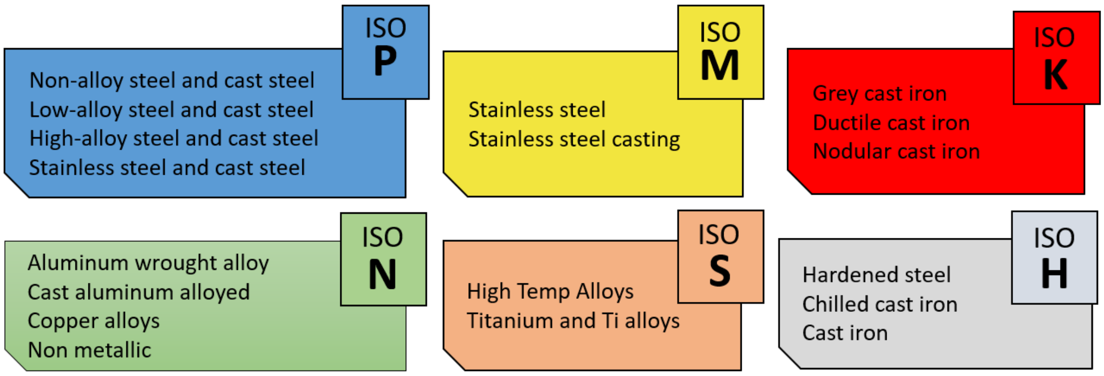

Figure 2.8 Workpiece material ISO groups

2.2. Available data information

In section 2.1 was introduced the tool-insert features for a general model insert. These features represent the own characteristics of a tool-insert in relationship to both working conditions and cutting parameters. These relations are plenty defined on the tool supplier website as product data tables.

Table 2-1 Product data from Sandvik Coromant website for insert features

Ordering Code	CCMT 06 02 08-PM 4335	
Name feature	**ID feature**	**Value**
Material classification	ISO Group	ISO-P
Grade	GRADE	4335
Insert size and shape	SIZESHAPE	CC0602
Insert shape	SC	C
Nose angle	ANGLE	80°
Clearance angle	AN	7°
Corner radius	RE	0.794mm
Insert thickness	S	2.381mm
Hand	HAND	N
Substrate	SUBST	HC
Coating	COAT	CVD Ti(C,N) + Al2013 + TiN
Operation type	CTPT	Medium
Inscribe circle	IC	6.35mm
Cutting edge	LE	5.648mm

Wiper edge property	WEP	false
Recommended depth of cut	ap_rec	0.64mm (0.4-2.4)
Recommended feed rate	fn_rec	0.15mm/r (0.08-0.23)
Recommended cutting vel.	vc_rec	265m/min (320-230)
Weight	WT	0.0009kg

The Table 2-1 shows the available product data for the insert CCMT 06 02 08-PM 4335 as an example. These data show the features of such tool-insert. Nevertheless, it is important to note this data is based on recommended cutting parameters and it is not considering the working material properties.

On the tool supplier website is also published an online application called ToolGuide™. This application allows evaluating the working material properties, feed rate and grade insert to obtain a recommended cutting velocity.

Table 2-2 Cutting velocity data from ToolGuide™

Name feature	**ID feature**	**Value**
Recommended Cutting Velocity	vc_rec	101m/min
Working Conditions		
Grade	GRADE	1020
Feed rate	fn_rec	0.5mm/r
ISO group	ISO Group	ISO-P
Material classification	Low-alloy	P2.1.Z.AN
Hardness	HB	175 HB

The Table 2-2 shows the evaluation of a certain working conditions for a recommended cutting velocity parameter. It is important to note, the working conditions can be varied as long it is used different features values, i.e. different feed rate, material classification, hardness, grade insert, etc.

The tool-inserts product data and the cutting velocity next to its working conditions are the framework to build the dataset for this research. Thus, two datasets are proposed, one dataset which relates the cutting parameters to insert features and the other one which relates the working material to cutting parameters. The Table 2-3 and Table 2-4 introduce the variables for each dataset.

Table 2-3 Initial dataset for working material & cutting parameters

Number of Observations	4250	**Number of features**	4
Features Details			
Name	**Type**	**Description**	
GRADE	Factor	Insert Grade	
fn_rec	Numeric	Recommended feed rate	
Material	Factor	ISO group material	
HB	Numeric	Hardness material	

Table 2-4 Initial dataset for insert features & cutting parameters

Number of Observations	3832	**Number of features**	13
Features Details			
Name	**Type**	**Description**	
OrderingCode	Factor	Internal Insert Code	
CTPT	Factor	Cutting removal operation	
ICmm	Numeric	Inscribed Circle	
SC	Numeric	Shape Insert Angle	
LEmm	Numeric	Cutting length	
REmm	Numeric	Nose Radius	
WEP	Logical	Wiper property	
GRADE	Factor	Insert Grade	
Smm	Numeric	Thickness	
Material	Factor	ISO Group Material	
AN	Numeric	Clarence Angle	
ap_rec	Numeric	Recommended depth of cut	
fn_rec	Numeric	Recommended feed rate	

2.3. Database analysis

The last section introduces the initial datasets for this research. Nevertheless, some of the described features must be mapped before since these are used like inputs variables for the neural network models later. The mapped features must be represented numerically and defined independently each other.

The CTPT feature, which describes the cutting operation, is defined by three possible configurations: FINISHING, MEDIUM and ROUGHING operation. Consequently, the mapping for this feature is the One-hot state representations. The Table 2-5 CTPT feature mapping shows the mapping configuration for the CTPT feature.

The WEP feature, which defines if the tool-insert has a wiper radius in its design, is a logical features. For that, the mapping for this features is the transformation of TRUE to 1 and FALSE to 0.

Table 2-5 CTPT feature mapping

Name	Finishing	Medium	Roughing
Finishing	1	0	0
Medium	0	1	0
Roughing	0	0	1

Another import consideration for the dataset is about the working material. The Figure 2.8 shows the six available working material ISO groups. But, for each ISO group is defined specific geometrical features which deal with chip evacuation issues. In fact, each ISO group has own geometrical designs since each material produces a different machining chips [25]. Since this premise, it is possible to cluster the dataset for each ISO Group material. Then, these clusters represent different relations in its features. For that reason, the proposed model in the hereto research considers only the ISO P Group material to show this approach.

The Figure 2.9 shows three cluster data P, S and N ISO Group, Furthermore, for each cluster in the figure is shown a different relationship between ap_rec (depth of cut) and fn_rec (feed rate).

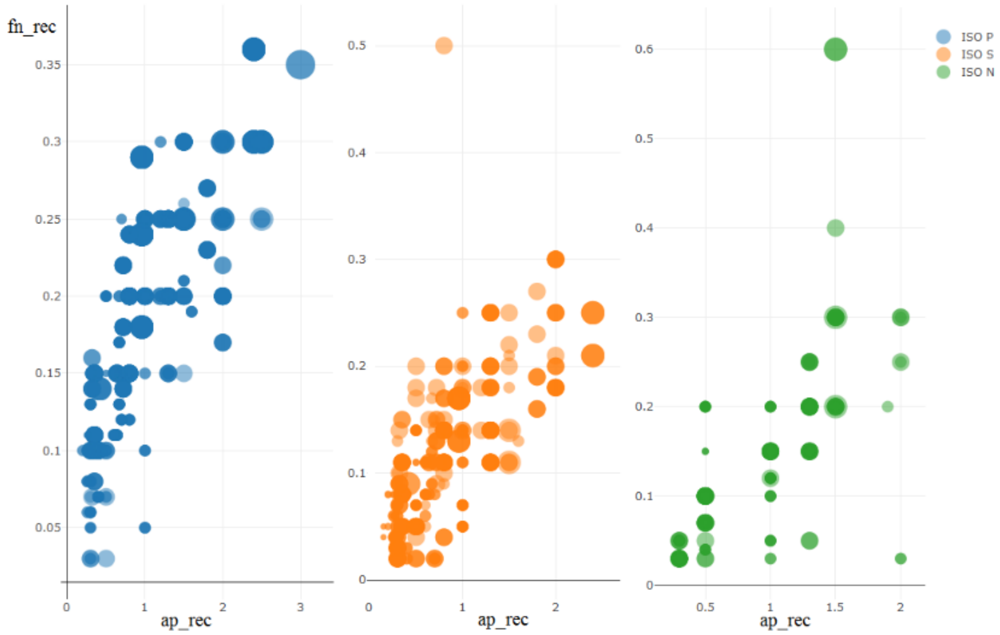

Figure 2.9 Depth of cut & feed rate by clustered ISO Groups

The GRADE feature, which describes the material composition of a tool-insert, must be also mapped to new features in order to completely represent the information behind of cutting tool composition. Figure 2.10 shows a graphical representation of the GRADE feature, nevertheless, not all the grades are considered for this model, instead, only the grades for which its information is available and also there are plenty of observations in the present dataset. Based on that conjecture, the Table 2-6 shows the selected Grades for the final dataset. Additionally, the Figure 2.11 shows a combined histogram for the selected grades and the cutting operation feature in order to give an insight about the data distribution.

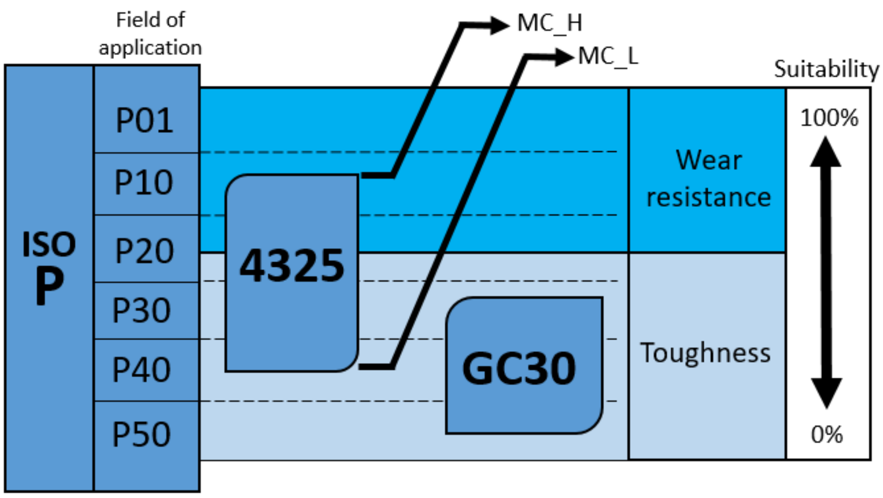

Figure 2.10 Grade feature definition for ISO P materials

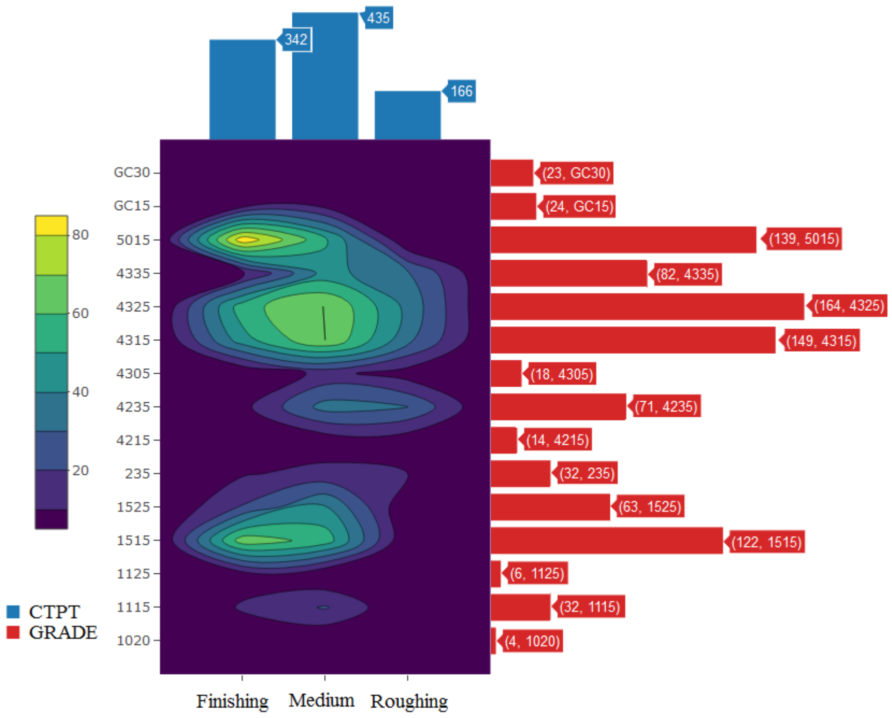

Figure 2.11 GRADE & CTPT features in a combined histogram

Table 2-6 Grade feature description

GRADE	MC_L	MC_H	Suitability
1125	10	30	75%
1515	10	30	75%
1525	5	25	100%
235	30	50	0%
4215	0	30	83.3%
4225	10	40	50%
4235	20	45	20%
4305	0	15	100%
4315	0	30	83.3%
4325	10	40	50%
4335	20	50	16.6%
5015	0	20	100%
GC15	15	25	100%
GC30	35	45	0%

The Table 2-6 introduces three new features which are linked to each grade in the dataset. These features describes the distribution of each grade in the range of area application for ISO P group material. The introduced features are MC_L, MC_H (machine condition LOW and HIGH respectively) and Suitability. The Figure 2.10 defines graphically these concepts.

The MC_L and MC_H features represent the low and high border of each grade in the range of area application. For instance, the grade 4325 is defined in MC_L = 40 and MC_H =10. Furthermore, the Suitability feature is defined as a percentage of range for each grade, which belongs to wear resistance region, i.e. in the upper region of the total field of application. Thus, the grade 4325 has 50% of suitability, rather the grade GC30 is defined as 0% of Suitability since it is totally defined in the lower region.

Considering the cutting velocity dataset at the Table 2-8 Cutting velocity – Features description was clustered only the material MC, group P1. This material group is also called unalloyed steel. This kind of workpiece material presents a carbon content usually by 0.8%, which is highly related to the hardness material, moreover, the hardness material varies from 90 up to 350HB [27]. It is important to mention, the thermal treatment and manufacturing process also condition the hardness material, but it was not considering since it is out of the scope of this research.

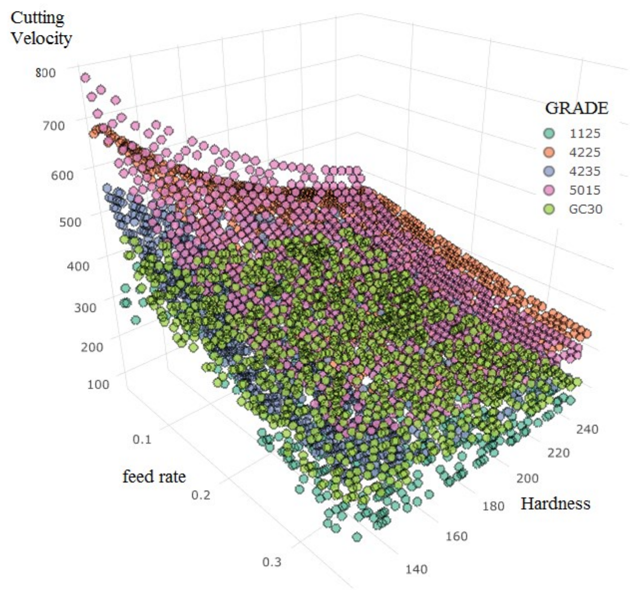

Figure 2.12 Cutting velocity, hardness and feed rate scatter

The Figure 2.12 shows graphically the working material dataset which represents the relation between working material, i.e. hardness feature; cutting parameters, i.e. feed rate and cutting velocity. It is important to note that relation varies as a function of insert Grade feature too.

2.4. Final dataset description

In last section was introduced all of the assumptions around to the initial dataset in order to sort it. In fact, some features were added to define the insert features and working conditions in better ways. Another achieved goal for the last section was the mapping transformation for some features in the dataset. This section aims to present the final datasets which are used to the neural networks model later.

Table 2-7 Feed rate dataset – Feature descriptions

Name	Type	Description
Number of Features		14 features
Observation		907
ICmm	Numeric	Inscribed circle
LEmm	Numeric	Cutting length
REmm	Numeric	Nose radius
WEP	Logical	Wiper property
Smm	Numeric	Thickness
AN	Logical	Clarence angle
ap_rec	Numeric	Recommended depth of cut
Angle	Numeric	Shape insert angle
Finishing	Logical	CTPT finishing operation
Medium	Logical	CTPT medium operation
Roughing	Logical	CTPT roughing operation
MC_L	Numeric	Low machine condition
MC_H	Numeric	High machine condition
MC_Suitability	Numeric	Suitability machine condition

There are two proposed datasets for this approach, a dataset for insert features with cutting parameters, and working conditions with cutting parameters. The first dataset will be used to train a model which infers feed rate, rather the second one will be used to model cutting velocity. The description for each dataset is shown at Table 2-7 and Table 2-8.

Table 2-8 Cutting velocity – Features description

Name	**Type**	**Description**
Number of Features		5 features
Observation		5000
fn_rec	Numeric	Recommended feed rate
HB	Numeric	Hardness material
MC_L	Numeric	Low machine condition
MC_H	Numeric	High machine condition
MC_Suitability	Numeric	Suitability machine condition

Chapter 3 Artificial neural network models

An artificial neural network model is powerful method to deal with non-linear functions or modeling systems with unknown input-output relations [28]. In fact, the purpose of this algorithm in hereto research is to find two models which relate the tool-insert features and working conditions to cutting parameters.

There are some important issues in the implementation of a neural networks model. These issues come from the facts of how a neural network model works. Since a neural network model considers non-lineal combinations and often uses gradient descent algorithm to update its parameters, the main issues is to reach a global solution instead of a local. Furthermore, given in fact a neural network model is built on the available dataset, the irrelevant, non-numerical and poor representation of input features can badly affect the final model. [29]

As an algorithm of machine learning, the neural network models have its main stone in the validation stage. For that reason, the error validation represents itself as the proof that the embedded information in the database is well represented by the reached model. For neural network models, some concepts are related to the validation stage, like overfitting, homogeneous representation and accuracy. [30]

The following are few considerations which were taken to implement the neural network models for this research.

3.1. Dataset preparation

For a neural network model, the dataset plays an important role. In fact, an effective preparation of data can lead to increase the accuracy, reduce the computing time, and prevent the overfitting in the model. [31]

For the dataset in this research, two scaling methods were considered to prepare the data for the training stage. The independent variables, which define the model inputs, have a scaling method called z-score. The dependent variables, which describes the output for the neural network model, have a scaling method based on its minimum and maximum values, which lead to a range from 0 to 1. [31]

$$x_{i-scaled} = \frac{x_i - mean(x)}{\sigma(x)} \tag{3-1}$$

$$y_{i-scaled} = \frac{y_i - \min(y)}{\max(y) - \min(y)} \tag{3-2}$$

The equations (3-1) and (3-2) show z-score and range scaling for inputs and outputs respectively. It is also important to note the output for a neural network model is highly depended on the activation function which is defined in the last layer (output layer). Generally, the activation function for the last layer is usually defined by hyperbolic tangent, softmax or even sigmoid function, which have an output range from 0 to 1. There are others activation functions wide used for neural network models, but for this research a lineal function was selected.

3.2. Architecture and error validation

The architecture and error validation are closely linked each other, in fact, the performance of a neural network model is defined by its architecture, but this last one is selected by the error validation. The architecture refers to the set parameters which govern complexity in the model, i.e. number of neurons and layers, updating and regularization algorithms, etc. Rather, the error validation refers to a procedure evaluation for a certain architecture in order to balance between accuracy and error distribution without falling in overfitting [32].

In practical application, training and testing dataset are used to achieve an architecture model which represent almost all of the information in the dataset. The training data is used to teach the model about the input-output relations. Furthermore, the testing data validates the model in order to represent most the total spectrum of possibilities in the dataset. For the present research, the databases for feed rate and cutting velocity model, which were described in section 2.4 (at Table 2-7 and Table 2-8), are divided in a ratio of 0.5 for training and testing validation.

The algorithm to converge the weights in a neural network model also plays an important role in the architecture. For this implementation, a globally convergent training scheme based on the resilient propagation is used. A crucial advantage about this algorithm instead of traditional back-propagation or normal resilient propagation is the computing time, as well, this approach shows a better accuracy performance with similar datasets to the used for this research; it means, a datasets which are compounded by factors and numerical mapped values. (See the chapter 2). [29]

The most important part in an error validation is the definition of a good performance which qualify the architecture of a neural network model. For this approach, the traditional root mean square error comparison was not only considered to validate the models [32]. Instead, the error validation for this research is defined by the comparison of error density functions for training and testing evaluations.

The error density functions are continuous functions which represent the reached errors for training and testing evaluations by a known function. The Gaussian function is used to represent these density functions. In such a way, the training and testing evaluations can be represented by a Gaussian error density function. It is important to note a Gaussian function is defined by two parameters, mean or expectation and standard deviation. For this approach, the expectation value is zero, furthermore the whole range of errors in the validation is defined into +/- 3 standard deviations by its definition.

Under this premise, a certain trained model will present a certain Gaussian density function; for such a reached model, a good performance should be defined by a testing Gaussian density function similar to the reached in training stage.

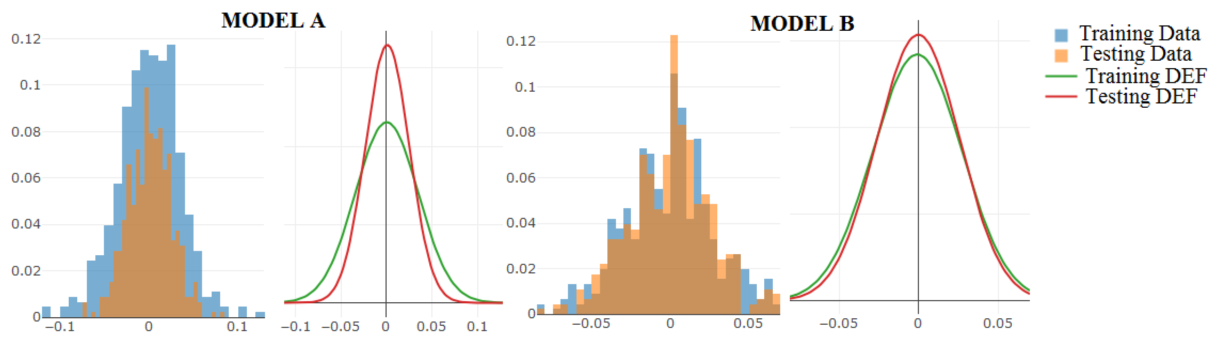

Figure 3.1 Error density function comparison example

For instance, the Figure 3.1 shows two models (model A and model B) which evaluate different architectures for feed rate model as an example. The model "A" shows a testing evaluation with a particular density function which is too different to reached one at training evaluation. Rather, the model "B" shows a testing error density performance quite similar to the reached at training evaluations.

The Table 3-1 shows numerically the same concept shown at the Figure 3.1. The Table 3-1 also shows additional error comparisons, i.e. the root mean square error (RMSE), median absolute deviation (MAD), maximum and minimum error values, etc. It is important to note, the large differences between root mean square error and median absolute deviation defined a skew indicative in the error density function [30].

Table 3-1 Error validation example

	Model A		**Model B**	
Properties	**Training Data**	**Testing Data**	**Training Data**	**Testing Data**
Mean square error	11.9E-4	5.8E-4	7.8E-4	6.7E-4
Root mean square error	34.5E-3	24.2E-3	28.0E-3	25.9E-3
Median Absolute Deviation	22.4E-3	16.7E-3	18.2E-3	16.7E-3
Max. Value	0.1275	0.0811	0.0698	0.0675
Min. Value	-0.1167	-0.0791	-0.0828	-0.0828
Mean	19.4E-5	87.0E-5	-8.0E-4	-1.8E-4
Standard Deviation	34.5E-3	24.2E-3	28.0E-3	26.0E-3

In order to achieve the best model for feed rate and cutting velocity, the following strategy was implemented to validate any possible architecture:

1. Consider random architectures with one and two hidden layers with different neurons per layer. Hereinafter is referred as architectures.
2. For each architecture, the training and testing error density functions are obtained. Hereinafter these Gaussian functions are referred as m_1, m_2
3. For each architecture, an Euclidean distance is evaluated between the function m_1, m_2. That Euclidean distance is calculated with the properties described in the Table 3-1. The equation (3-4) shows the implementation of this Euclidean distance.
4. For each architecture, the maximum distance between the mean error values to zero is considered. The equation (3-5) shows the implementation of this distance as the maximum absolute value of the mean property in testing and training error functions.
5. A maximum range of the error functions must be calculated. That range is defined by the maximum and minimum properties for the each error function m_1, m_2. See equation (3-6)
6. In order to consider the skew property for the m_1 and m_2, the distance between root mean square errors to median absolute deviation is calculated. The equation (3-7) shows the implementation of this distance as the maximum absolute value for the difference between RMSE to MAD (root mean square error and median absolute deviation respectably) for both m_1 and m_2.
7. Then, the performance of a suggested model is given by the equation (3-3), which evaluates the Euclidean distance, mean distance to zero, the total error range and skew

distance as a function of m_1 and m_2. The constant k allows to adjust the function into a certain range of values.

$$F_{perfo}(m_1, m_2) = \frac{k}{d_{ED} \cdot d_{mean} \cdot d_{range} \cdot d_{skew}} \tag{3-3}$$

$$d_{ED} = \sqrt{\sum(m_1 - m_2)} \tag{3-4}$$

$$d_{mean} = \max(|mean_{m1}|, |mean_{m2}|) \tag{3-5}$$

$$d_{range} = \max(|\max_{m1} - \min_{m1}|, |\max_{m2} - \min_{m2}|) \tag{3-6}$$

$$d_{skew} = \max(|RMSE_{m1} - MAD_{m1}|, |RMSE_{m2} - MAD_{m2}|) \tag{3-7}$$

In order to validate several random architectures, a heuristic optimization search was implemented by using genetic algorithm for feed rate and cutting velocity models. These architectures differ each other in layer and neuron numbers, furthermore, this genetic algorithm is defined by the equation (3-3) as a fitness function. The model performance for the reached models are shown by Table 3-2. These model was obtain after a certain number of epochs (generations), in each epoch the heuristic algorithm select, cross and mutate architecture models in order to reach the best one which evaluates the best performance given by the fitness function. It means the best architecture.

Table 3-2 Error validation for feed rate and cutting velocity models

	Feed Rate		**Cutting Velocity**	
	Training	**Testing**	**Training**	**Testing**
Architecture	15 - 4		15 – 5	
Mean square error	4.95E-4	3.45E-4	57.71	66.66
Root mean square error	2.22E-2	1.8E-2	7.59	8.16
Median Absolute Deviation	1.41E-2	1.10E-2	3.84	3.91
Max. Value	5.82E-2	5.82E-2	102.82	95.51
Min. Value	-6.97E-2	-6.71E-2	-52.76	-75.10
Mean	-1.73E4	1.24E-4	-3.60E-2	-3.61E-2
Standard Deviation	2.22E-2	1.86E-2	7.59	8.16
d_{ED}	6.55E-3		25.16	

d_{mean}	1.73E-3	3.61E-2
d_{range}	1.28E-1	170.61
d_{skew}	8.14E-3	4.25
k	1E-6	1E5
F_{perfo}	845.26	151.68

The Table 3-2 shows the reached architectures for feed rate and cutting velocity models. For feed rate, a neural network model with 2 hidden layers was stablished. Furthermore, this model has 15 and 4 neurons per layer. While cutting velocity model was also established with 2 hidden layers but 25 and 7 neurons per layer instead. The graphical performance for both models are shown in the Figure 3.3 and Figure 3.4 (feed rate and cutting velocity respectively). In these figures is possible to appreciate the error density function in training and testing evaluation. That figures also show the reached genetic algorithm performance used to converge both models. It is important to note the optimization by genetic algorithm allows to achieve a good performance for both models in a short time of iterations that otherwise the total combination of neurons and layers, per each model, would have taken more evaluations and computing time. Finally, the Figure 3.2 and Figure 3.5 show the graphical neural architectures for feed rate and cutting velocity models respectively.

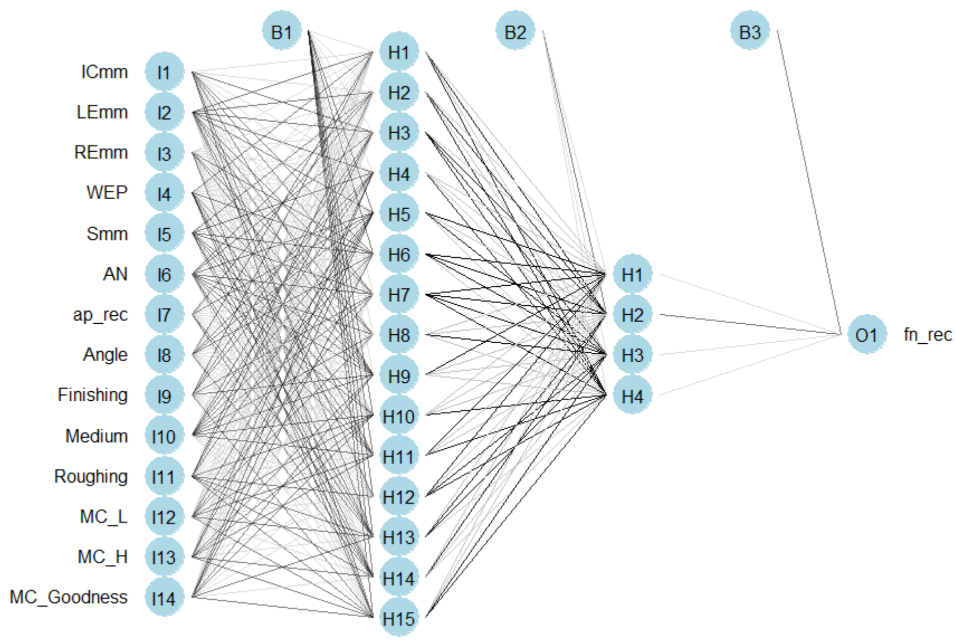

Figure 3.2 Neural network architecture for feed rate model

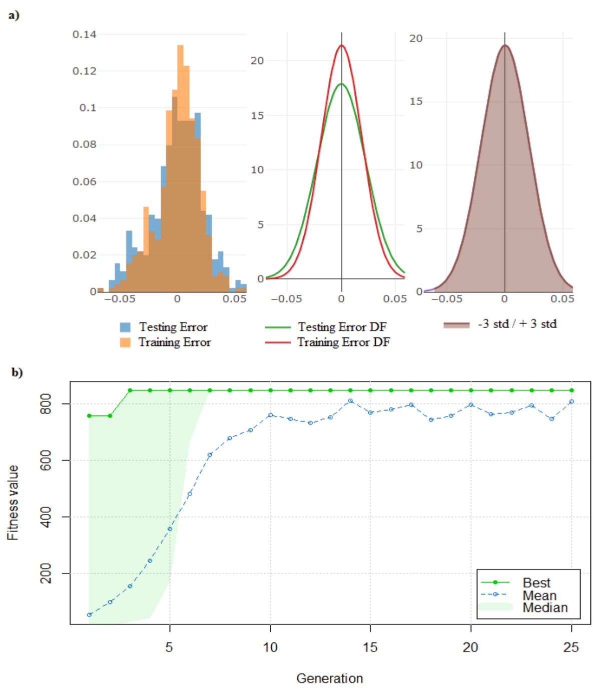

Figure 3.3 Feed rate model performance; a) Error density function comparison; b) Genetic algorithm performance

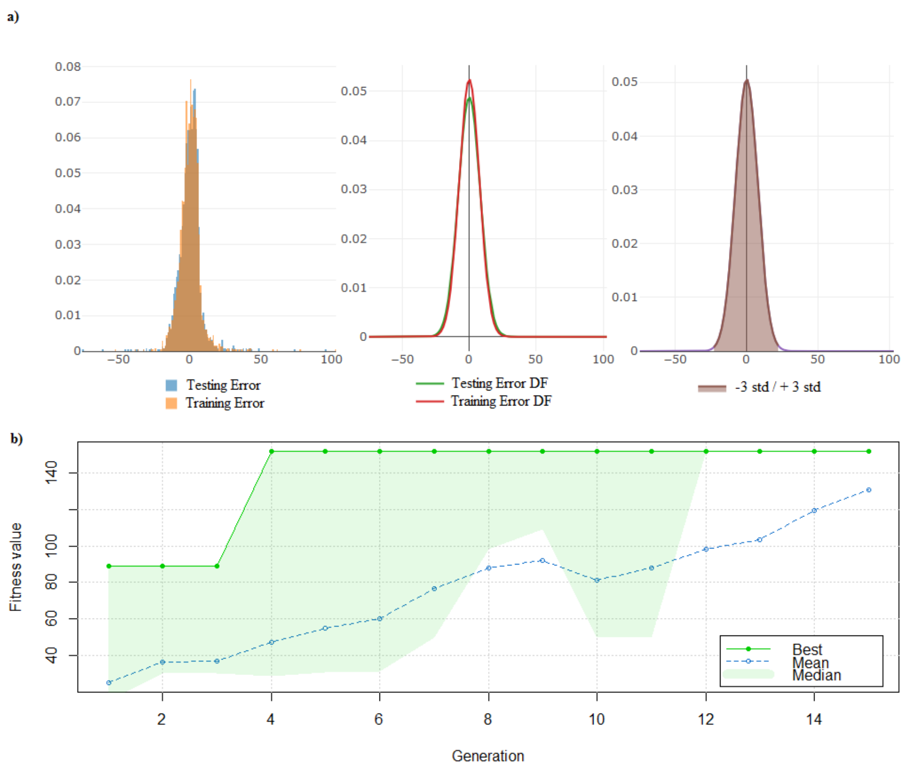

Figure 3.4 Cutting velocity model performance; a) Error density function comparison; b) Genetic algorithm performance

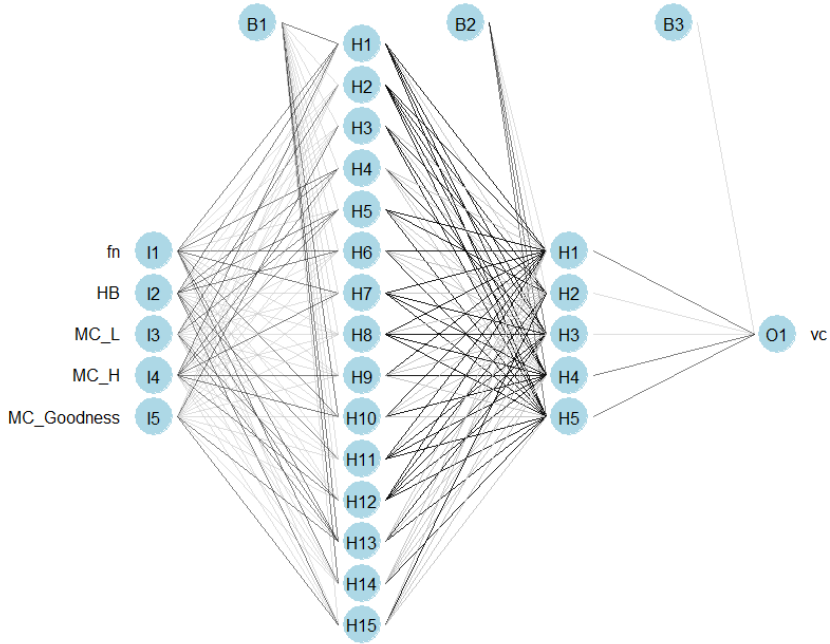

Figure 3.5 Neural network architecture for cutting velocity

Chapter 4 Genetic algorithm optimization

A Genetic Algorithm, hereinafter referred as GA, is a heuristic search algorithm inspired on evolutionary mechanisms and biological natural selection. This algorithm defines a searching space of solutions and allows to find individuals which fit to a certain condition called fitness function. [33]

The present chapter aims to define a heuristic search based on GA which allows to find an optimal insert-tool for a certain working specifications. This insert-tool searching is governed by a fitness function, which is defined by the lowest power consumption, the shortest machining time, acceptable surface roughness, etc.

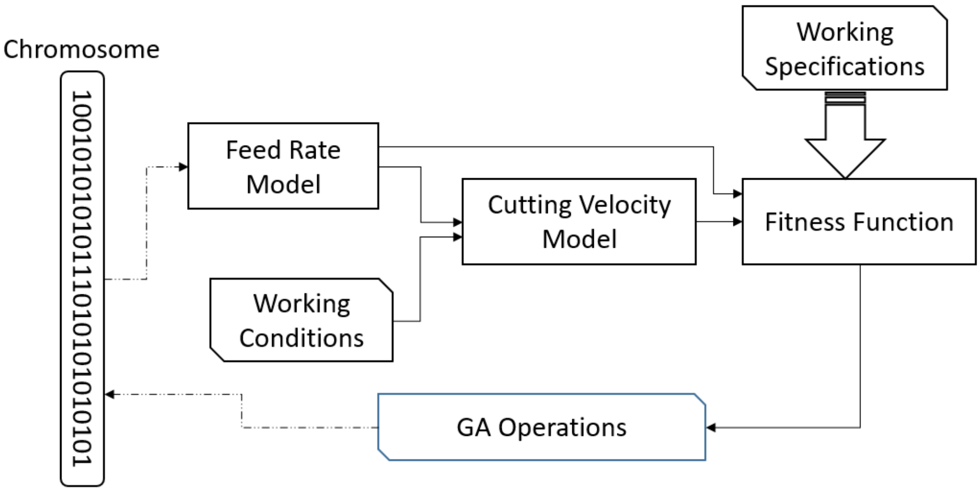

Figure 4.1 GA Working scheme

The Figure 4.1 shows a general scheme of the GA implementation proposed for this research. Initially it is possible to appreciate that the GA chromosome is evaluated by the feed rate model. Then, the feed rate and working conditions represent the inputs for the cutting velocity model. Thus, the resulting feed rate and cutting velocity are evaluated by the GA fitness function, which next to the working specifications qualify the current chromosome. Finally, the GA operations transform the current population to the next generation. In such a way according their characteristics, the individuals in the population are getting better by each iteration.

The following is shown a detailed information for this optimization algorithm, since the definition of the working specifications, chromosome definition, fitness function, performance and implementation.

4.1. Working specifications

The working specifications for a GA are the framework which define the optimization problem. For this research, the working specifications are compounded by 3 groups: materials conditions, machine conditions and general specifications. The Table 4-1 introduces these categories for this working specifications.

Table 4-1 Working specifications

Material specification		
Initial Diameter	D_i	Numeric values
Final Diameter	D_f	Numeric values
Machining Length	L_m	Numeric values
Hardness	HB	Numeric values
Specific Cutting Force	K_c	Numeric values
Max. Surface Roughness	$R_{a\_\max}$	Numeric values
Machine specification		
Main Motor Power	P_{net}	Numeric values
Maximum Spindle speed	$n_{\max}$	Numeric values
General conditions		
Machine Operation	$CTPT$	Finishing – Medium – Roughing
Stability	----	Excellent – Good - Poor
Toot Life	T_{life}	Numeric values
Threshold Distance	Th_d	Numeric values

The material specification represents the conditions related to the working piece. For instance, the initial and final diameter, the maximum surface roughness allowed, the machining length. Furthermore, the mechanical properties are also added to this group, i.e. material harness and specific cutting force.

On the other hand, the machine conditions represents the relevant information of the CNC machine in a turning operation. For this approach, the total power available and the maximum spindle speed are considered.

The general conditions defines additional specifications which also define a turning operation. For instance, the machine operation is considered into this group of specifications. This condition defines the CTPT feature which set to the algorithm if the insert-tool solution should be for finishing, medium or roughing operation. Furthermore, the stability parameter is also added to this group of specifications. This stability feature is related to the Suitability feature for the expected insert-tool solution.

Finally, the tool life and threshold distances are defined as tuning constants which allow to adjust the accuracy of the algorithm. These last parameters are deeper explained in section 4.3 Fitness function.

4.2. Encode-decode chromosomes

A binary chromosome refers to a string of zeros-ones, such as a binary number, which represents a certain bunch of features. The introduced Table 2-7 Feed rate dataset – Feature descriptions, in the section 2.4, shows the description of the used features for the chromosome structure. On the other hand, each feature has its own encoding length in order to be well represented in the chromosome string. The Table 4-2 shows the features which are used to build the GA chromosome and their binary length.

Table 4-2 Insert features description for decoding procedure

Name	Type	Range	Length of binary no.
ICmm	Numeric	15.875 – 3.970	4
LEmm	Numeric	21.20 – 5.65	4
REmm	Numeric	1.19 – 0.02	7
WEP	Logical	1 - 0	1
Smm	Numeric	5.56 – 1.98	7
AN	Logical	7 - 5	1
Angle	Numeric	90 – 35	6
Stability	Factor	*no defined	NA
ap_rec	Numeric	*no defined	7

The length properties in the Table 4-2 represents the length of the binary number used to define each feature. Furthermore, for the described numeric features are defined a specific decode procedure called lineal transformation which is represented by the equation (4-1). For this equation, the binary number is evaluated by the function $\text{int}(X_{binary})$, which returns the integer value for such binary number. Then, that integer value is mapped by the maximum, minimum and length values in order to decode the corresponded feature.

$$X_{real} = X_{\min} + \frac{X_{\max} - X_{\min}}{2^{length} - 1} \cdot \text{int}(X_{binary}) \tag{4-1}$$

The logical features described in the Table 4-2 use only one digit to be represented since they have only 2 possible values (1-0 and 5-7 for WEP and AN features respectively).

Finally, the Stability feature have a decoding and encoding procedures which differ from the rest of features. The stability features refers to the suitability feature of an insert-tool. That feature can be set as Excellent, Good, or Poor. That definition was introduced in the Figure 2.6 Insert grade feature at the section 2.1 Introduction to cutting insert features. Actually, that parameter is already given by the working specification described in Table 4-1. But, this information conditions the GA searching space since the grade of an insert-tool is defined under a certain range of application area. That means, there are only a bunch of Grades for a defined stability feature. The Table 4-3 shows the stability condition associated to the insert-tool grades in the present dataset.

Table 4-3 Grade stability

GRADE	Suitability	Stability
1125	75%	Good
1515	75%	Good
1525	100%	Excellent
235	0%	Poor
4215	83.3%	Excellent
4225	50%	Good
4235	20%	Poor
4305	100%	Excellent
4315	83.3%	Excellent
4325	50%	Good

4335	16.6%	Poor
5015	100%	Excellent
GC15	100%	Excellent
GC30	0%	Poor

Under this premise, the proposed encoding procedure for the features stability is defined by a grades list (Indexed list) and a binary number which indexes the position for each grade in such list. For instance, consider the stability "Good" described by the Table 4-4. Since there are only 4 possible Grades in that condition, the binary number to encode this feature is a string of 3 digits (000, 001, 010, 011, 111, etc.). Then, the number of ones in such binary number represent the index in the Grade list. For 2 ones in the binary number then the grade is 4225, for 0 ones in the binary number then the grade is 1125, etc.

Table 4-4 Indexed list for good stability

Index	**GRADE**	**Stability**
0	1125	Good
1	1515	Good
2	4225	Good
3	4325	Good

The ap_rec cutting parameter is a special feature for the chromosome definition. The rage of this parameter is defined previously as an input of the model. This range is customized by the total and minimum depth of cut value for a certain turning process. Such values are defined regarding operation issues and specific requirements.

The chromosome structure for the GA optimization is shown in the Figure 4.2. This structure defines at least 30 defined positions. It is important to note, each feature has its binary position and length into the chromosome structure. That portion of strings defines the characteristic of the GA individual to heritage to the next generation.

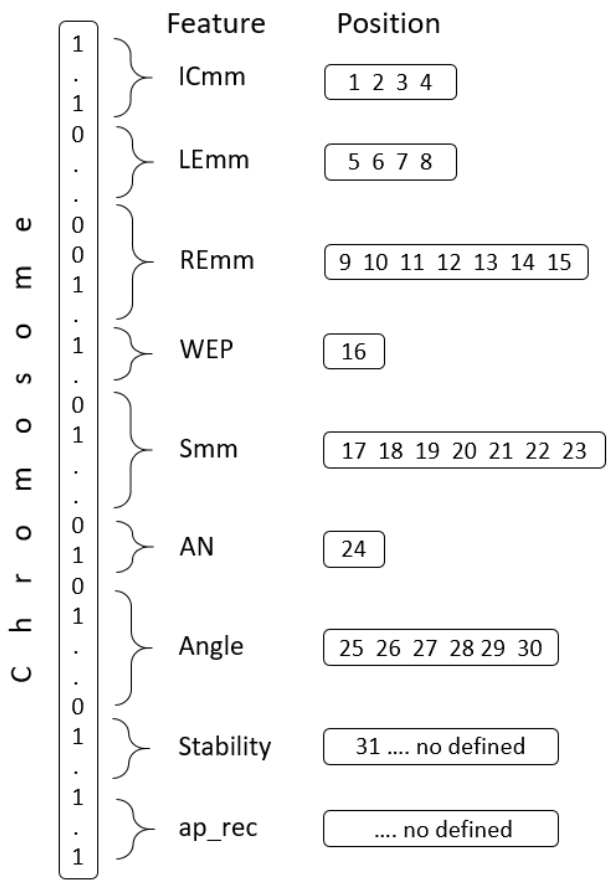

Figure 4.2 Chromosome structure

4.3. Fitness function definition

The fitness function is the main stone for the Genetic Algorithm. In Fact the definition of this functions stablishes the expected output of the algorithm. For this research, it was defined an objective function which evaluates the lowest power consumption, the shortest machining time, an acceptable surface roughness, etc. This fitness function is also evaluated into a working specifications which were introduced in section 4.1 Working specifications.

$$fitness = \sum_i \omega_i \cdot g_i \tag{4-2}$$

The equation (4-2) defines the fitness function for this genetic algorithm optimization. This equation is a summation of goal functions $g_i(f)$ which evaluate power consumption, machining time, surface roughness, etc. Furthermore, each g_i function is weighted by a constant ω_i, which allows to adjust the importance of each g_i function face to other ones.

$$g_1 = \frac{\gamma \cdot P_{net}}{P} \tag{4-3}$$

$$P = \frac{v_c \cdot F_c}{6 \times 10^4} \tag{4-4}$$

$$F_c = K_c \cdot ap\_rec \cdot fn\_rec \tag{4-5}$$

The goal function g_1 described by equation (4-3) evaluates the power consumption ratio in the turning process. That function uses the equation (4-4) to evaluate the theoretical power consumption P [20]. Furthermore, the P_{net} constant is the total available power in the machine which was introduced at the Table 4-1. Moreover, the γ constant allows to consider the friction losses in the transmission motor [20], nevertheless this constant is equal to 1 for this approach.

The equation (4-5) shows the cutting force F_c as a function of the specific cutting force K_c related to the working material, depth of cut ap_rec, and feed rate fn_rec [27]. It is important to note the specific cutting force K_c is a parameter which was also set by the Table 4-1.

$$g_2 = \frac{T_{life}}{T_m} \tag{4-6}$$

The goal function g_2 described by the equation (4-6) defines the machining time ratio, which relates the tool life to the machining time. The tool life T_{life} is a tool supplier parameter which defines the approximate tool life for a tool-insert. The machining time is an objective variable evaluated by the equation (4-7) which defines the machining time in the turning process with a certain group of cutting parameters. Furthermore, the equation (4-8) presents the spindle speed n as a function of cutting velocity v_c and the current machining diameter D. It is important to note the spindle speed n varies according to the machining diameter D. Thus, for each pass machining (diameter decreasing) the spindle speed increase.

$$T_m = \frac{L_m}{fn\_rec \cdot n} \tag{4-7}$$

$$n = \frac{v_c \times 1000}{\pi \cdot D} \tag{4-8}$$

The objective function g_3 defined by the equation (4-9) relates the maximum surface roughness $R_{a\_\max}$ to the theoretical reached surface roughness R_a. The parameter $R_{a\_\max}$ is a working specification of material which defines the maximum roughness allowed. While R_a is an objective variable defined by the equation (4-10) which estimates the surface roughness for a certain finishing operation. [20].

$$g_3 = \frac{R_{a\_\max}}{R_a} \tag{4-9}$$

$$R_a = \frac{125 \cdot fn\_rec^2}{REmm} \tag{4-10}$$

It is import to clear that such equation (4-10) does not take into account any additional insert geometries, such as tool WEP feature. Furthermore, this approach of surface roughness does not consider any tool vibration or chip adhesion [17].

$$g_4 = \frac{Th_d}{d_{euclidean}} \tag{4-11}$$

$$d_{euclidean} = \min \sqrt{\sum_i (x_i - y_i)^n} \tag{4-12}$$

The objective function g_4, defined by the equation (4-11), relates the objective variable $d_{euclidean}$ with the parameter Th_d called threshold distance. The variable $d_{euclidean}$ is obtained by the equation (4-12). The equation (4-12) returns the minimum Euclidean distance between the features x_i to the features y_i, which are defined by the suggested GA tool-insert features and the n^{th} tool-insert in the dataset respectively.

$$g_5 = \frac{n_{\max}}{n} \tag{4-13}$$

The objective function g_5 evaluates the spindle speed ratio used in the turning process. This objective function relates the maximum spindle speed for the machine to the theoretical spindle speed reached in the turning process.

$$g_6 = \frac{1}{MC\_H - MC\_L} \tag{4-14}$$

The objective function g_6 evaluates the suitability range for a certain insert grade. This function weights if a suggested grade is more appropriate for a specific application area than others solutions. The more specific grades are preferred instead of the general ones.

Overall, there are two fitness function regarding to turning processes which are finishing or roughing operations. In fact, for roughing operation the surface roughness is not considered into the fitness function, but power consumption, machining time, Euclidean distance, spindle speed ratio, and suitability are considered (goal functions (4-3), (4-6), (4-11), (4-13), and (4-14) respectively). Furthermore, for finishing process, the fitness function considers the surface roughness, Euclidean distance and suitability grade (equations (4-9), (4-6) and (4-14) respectively).

$$f_{roughing} = \omega_1 \frac{P_{net}}{P} + \omega_2 \frac{T_{life}}{T_m} + \omega_3 \frac{Th_d}{d_{euclidean}} + \omega_4 \frac{n_{\max}}{n} + \omega_5 \frac{1}{MC\_H - MC\_L} \tag{4-15}$$

$$f_{finishing} = \omega_1 \frac{R_{a\_\max}}{R_a} + \omega_2 \frac{Th_d}{d_{euclidean}} + \omega_3 \frac{1}{MC\_H - MC\_L} \tag{4-16}$$

The equation (4-15) and (4-16) show the proposed fitness function for roughing and finishing operation.

4.4. Boundary constraints

The boundary constraints for a GA optimization defines the searching space for the algorithm. These boundary constraints allow to control the chromosome evolution and ensure that the algorithm is converging toward a suitable solution.

The first mechanism to control the population evolution is called feasible solution control. This boundary control prevents that unfishable individuals appears in the population [20]. This mechanism evaluates the goal function g_4 by the constrain (4-17). In such a way, only similar insert-tools are chosen as part of the population. The unfishable solutions are not considered.

$$g_4 = \frac{Th_d}{d_{euclidean}} < 1 \tag{4-17}$$

Some boundary constrains are established to prevent solutions which evaluate parameter out of the machine capabilities. For instance, the expression (4-18) avoids GA individuals which evaluate power consumption out of the maximum for the machine. The constraint (4-19) avoids solutions which need spindle speed greater than the maximum defined for the machine. The solution out if the range are no considered into the GA population.

$$g_1 = \frac{\gamma \cdot P_{net}}{P} < 1 \tag{4-18}$$

$$g_5 = \frac{n_{\max}}{n} < 1 \tag{4-19}$$

4.5. Implementation

The present section aims to describe the whole optimization model. Such description introduces some key points in order to be used as a guide for action implementations. The Figure 4.1 shows a general scheme for the present model, nevertheless, some GA mechanisms were ignored for practical issues. A complete description of this GA optimization is shown at the Figure 4.3. In fact, that figure also describes some cross-references for each concept.

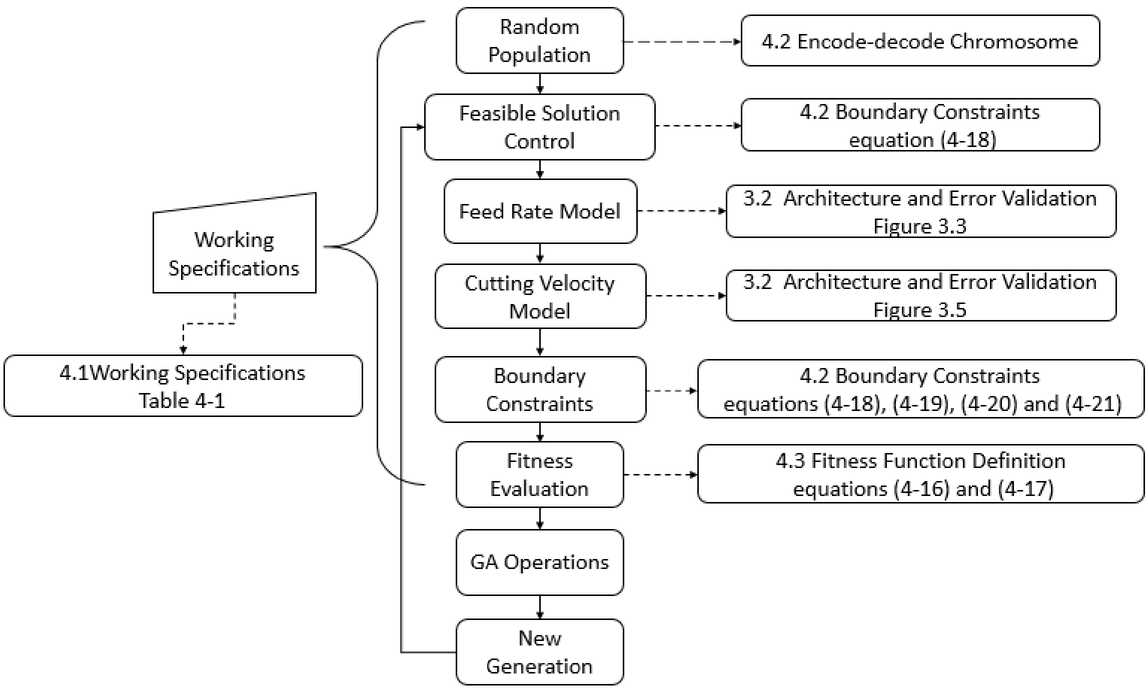

Figure 4.3 Flow chart for GA implementantion

In order to explain this GA optimization model, a practical application is also introduced along this section. Even though this application is a scenario for a roughing operation, the explained process is also applicable to medium and finishing operations as well.

The model begins with the definition of the working specifications, which is presented by The Table 4-5. This specifications set the framework for this example. It is important to note that the working specifications are related along the GA model to some stages forward, such as the random Population, Feasible Solution Control, Feed rate and cutting velocity models, boundary constraints, and fitness evaluation stage.

Table 4-5 Practical implementation – Working specifications

Material specification		
Initial diameter	D_i	50 mm
Final diameter	D_f	40 mm
Machining length	L_m	100 mm
Hardness	HB	180 HB
Specific cutting force	K_c	600 N/mm^2
Machine specification		
Main motor power	P_{net}	10 kW
Maximum spindle speed	$n_{\max}$	3000 rpm
General conditions		
Machine operation	*CTPT*	Roughing
Stability	----	Good
Toot life	T_{life}	15 min
Threshold distance	Th_d	10
range ap_rec	ap_rec	0.01 – 5 mm

The stability condition stablishes some insert grades as possible solutions since this specification was set at "Good" in the Table 4-5. Such grade solutions were already shown at Table 4-4 Indexed list for good stability. With the stability features already defined, the total chromosome length is defined to 40 for this example.

On the other hand, the insert features and working specifications which form the chromosome structure was introduced in the section 4.2 Encode-decode chromosomes at the Table 4-2. The Figure 4.4 describes a chromosome structure for this scenario.

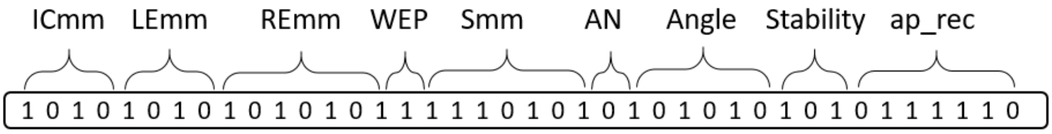

Figure 4.4 GA Chromosome example.

Give the random nature of the GA model, some infeasible individuals can be part of the population. For that, the feasible solution control avoids that unpractical solutions form part of the GA population. The implementation of this control was introduced in the section 4.4 Boundary constraints by the equation (4-17). This control evaluates an Euclidean distance adjusting the Th_d parameter. All of the individuals out the range of the distance are discarded of the GA population.

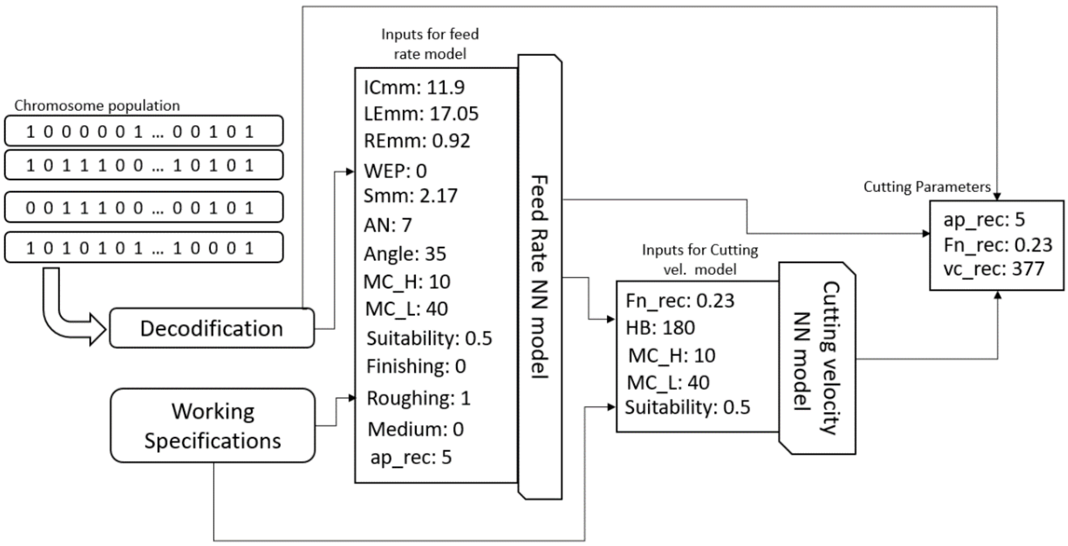

Figure 4.5 Neural networks models in the GA optimization

The Figure 4.5 shows the flow chart to obtain the cutting parameters given a chromosome individual in the population. It is import to note, some working specifications are used to both feed rate and cutting velocity neural network models. As well, the ap_rec cutting parameter (depth of cut) is defined by the GA chromosome and used in the feed rate model as an input. Once the cutting parameters ap_rec, fn_rec, and vc_rec are obtained is possible to evaluate the performance for the current chromosome. The equation (4-20) shows a proposed fitness function to evaluate the performance for each GA individual.

$$f_{roughing} = 100\frac{P_{net}}{P} + 0.5\frac{T_{life}}{T_m} + \frac{Th_d}{d_{eucliden}} + \frac{n_{\max}}{n} + \frac{100}{MC\_H - MC\_L} \tag{4-20}$$

The goal variables P, T_m, $d_{euclideanm}$ and n define power consumption, machining time, euclidean distance and speed spindle respectively. This objective variables are evaluated by the equations (4-4), (4-7), (4-12) and (4-8).

In line with Flow chart for GA implementantion, the Boundary Constraints establishes a population control again, which avoids that GA individuals evaluate parameters beyond the capabilities of the CNC machine. That constraints are related to the total power available and maximum speed spindle defined in the CNC.

Once the whole population has been qualified by the fitness function, the GA operation crosses, selects and mutates the chromosomes in order to evolve toward the next generation. After a new generation was reached the procedure starts since the Feasible Solution Control again. In such a way, after a certain number of iterations, the population has been evolved enough toward a suitable insert-tool solution with its cutting parameters.

Table 4-6 Practical application - Goal variables evaluation

Goal Variables		
Power Consumption	P	5.07 kW
Machining Time	T_m	0.34 min
Speed spindle	n	2741 rpm
High machining condition	MC_H	40
High machining condition	MC_L	10
From the dataset		
Closer Tool-Insert	------	VBMT 16 04 04-UR 4325
Recommended depth of cut	ap_rec	2 mm
Recommended feed rate	fn_rec	0.25 mm/r
Recommended cutting vel.	vc_rec	365 m/min
From the model		
Depth of cut	ap_rec	5 mm
Feed rate	fn_rec	0.294 mm/r
Cutting vel.	vc_rec	344 m/min

Euclidean distance	$d_{euclidean}$	4.7929
Fitness function	------	223.69

The Table 4-6 shows the evaluation of a suggested tool-insert. This tool insert is part of the solution of the most suitable tool-inserts in the dataset, which evaluate a higher fitness functions. At the same table is also shown the cutting parameters for such tool-insert, as well as, the goal functions for power consumption, machining time and speed spindle etc. which were evaluated for the suggested solution. It is important to mention, that solution is not the best one. It has been only chosen for practical issues.

Chapter 5 Design examples

This chapter aims to explain some practical applications using the algorithm described in this research. Three design examples are used to show the performance and results for this approach. This examples are defined under different working conditions and fitness functions. It is important to mention that a detailed implementation was already shown in the last chapter, at the section 4.5. But, some repeated concepts are quoted again for practical issues.

5.1. Light roughing operation example

For this example, a light roughing machining application can be defined as a turning operation with a small turning depth. In fact, these turning operations could be machined by only one pass. In this way, the described algorithm allows to find a tool-insert solution which balances both power consumption and number of passes. On the other hand, the machining time has not the same importance than power consumption since the number of passes are not much.

Table 5-1 Working Specifications for light roughing operation example

Material specifications		
Initial diameter	D_i	50 mm
Final diameter	D_f	40 mm
Machining length	L_m	100 mm
Hardness	HB	180 HB
Specific cutting force	K_c	600 N/mm^2
Machine specifications		
Main motor power	P_{net}	10 kW
Maximum spindle speed	$n_{\max}$	3000 rpm
General conditions		
Machine operation	$CTPT$	Roughing
Stability	----	Good
Toot life	T_{life}	15 min

Threshold distance	Th_d	10
range ap_rec	ap_rec	0.01 – 5 mm

$$fitness = 100\frac{P_{net}}{P} + 0.5\frac{T_{life}}{T_m} + \frac{Th_d}{d_{eucliden}} + \frac{n_{\max}}{n} + \frac{100}{MC\_H - MC\_L} \tag{5-1}$$

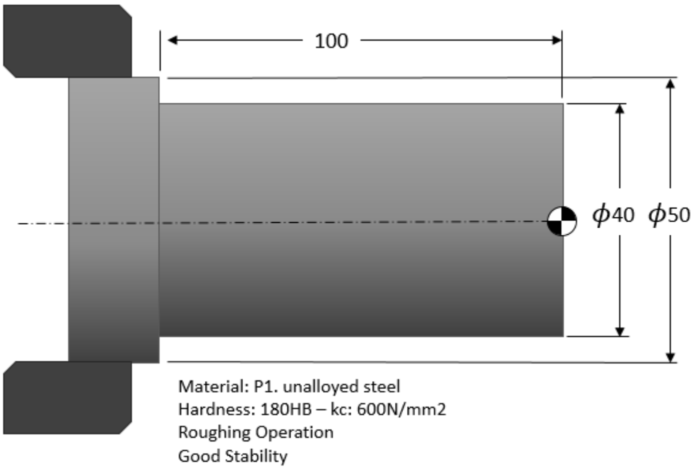

Figure 5.1 Light roughing operation example

The Table 5-2 introduces the working specifications for this light roughing operation. It sets an initial and final diameter to 50 mm and 40 mm respectively, which defines a total depth of cut of 5 mm, additionally, the total machining length is set to 100 mm. Furthermore, the Figure 5.1 shows this information graphically.

The workpiece material is an unalloyed steel of 180HB. That material has a specific cutting force of 600N/mm^2.

The machine specifications define a small lathe with a total power available of 10 kW and maximum speed spindle of 3000 rpm.

The equation (5-1) sets the fitness function for this operation. The power consumption has been weighted to 100 times, while the machining time to 0.5. That fitness function considers that the power consumption impacts more than the machining time during the turning process for this example.

Table 5-2 Results for the light roughing operation example

Features	GA Results	Closer insert
ICmm	8.73	6.35
LEmm	10.5	10.3
REmm	0.68	0.39
WEP	false	false
Smm	2.37	2.38
AN	7°	7°
Angle	65°	60°
GRADE	4325	4325
Cutting parameters		
Closer insert	TCMT 11 02 04-UR 4325	
Depth of cut	5 mm	
Feed rate	0.288 mm/r	
Cutting velocity	346 m/min	

The Table 5-2 shows the reached non-existent insert by the GA evolution next to the defined closer tool-insert in the dataset. It is also presented the reached tool-insert and its cutting parameters as well.

At the Table 5-3 is introduced the evaluation for the goal variables which define the performance for the suggested tool-insert. In this table is also shown the related equation for each goal variables.

Table 5-3 Goal variables evaluation for light roughing operation example

Goal variable	Variable	Equation.	Evaluation
Power consumption	P	(4-4)	5 kW
Machining time	T_m	(4-7)	0.34 min
Euclidean distance	$d_{euclidean}$	(4-12)	6.307
Speed spindle	HB	(4-8)	2761 rpm
High machining condition	MC_H	---	40
High machining condition	MC_L	---	10
Fitness function	$fitness$	(5-1)	225.69

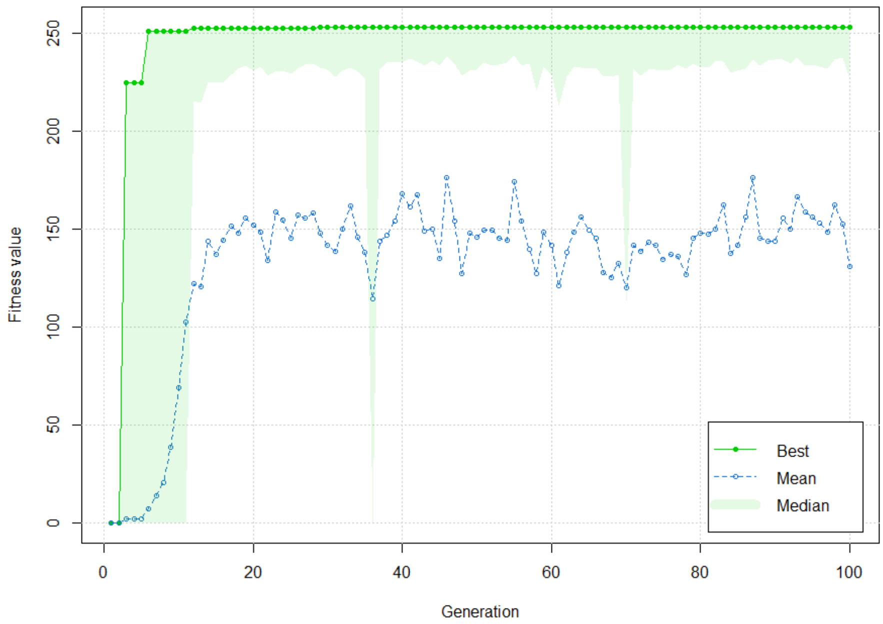

Figure 5.2 GA performance for light roughing operation example

5.2. Heavy roughing operation example

A heavy roughing application can be defined as a turning operation with a large depth turning. These turning operations cannot be machined by only one pass, in contrast with light roughing machining. For that reason, the fitness function for theses turning operations considers the machining time evaluation more than the power consumption.

Table 5-4 Working specifications for heavy roughing operation example

Material specifications		
Initial diameter	D_i	100 mm
Final diameter	D_f	40 mm
Machining length	L_m	100 mm
Hardness	HB	250 HB
Specific cutting force	K_c	$725\ N/mm^2$
Machine specifications		
Main motor power	P_{net}	10 kW
Maximum spindle speed	$n_{\max}$	3000 rpm

General conditions		
Machine operation	*CTPT*	Roughing
Stability	----	Good
Toot life	T_{life}	15 min
Threshold distance	Th_d	10
range ap_rec	ap_rec	0.01 – 5 mm

$$fitness = 0.5\frac{P_{net}}{P} + 10\frac{T_{life}}{T_m} + \frac{Th_d}{d_{eucliden}} + \frac{n_{\max}}{n} + \frac{100}{MC\_H - MC\_L} \tag{5-2}$$

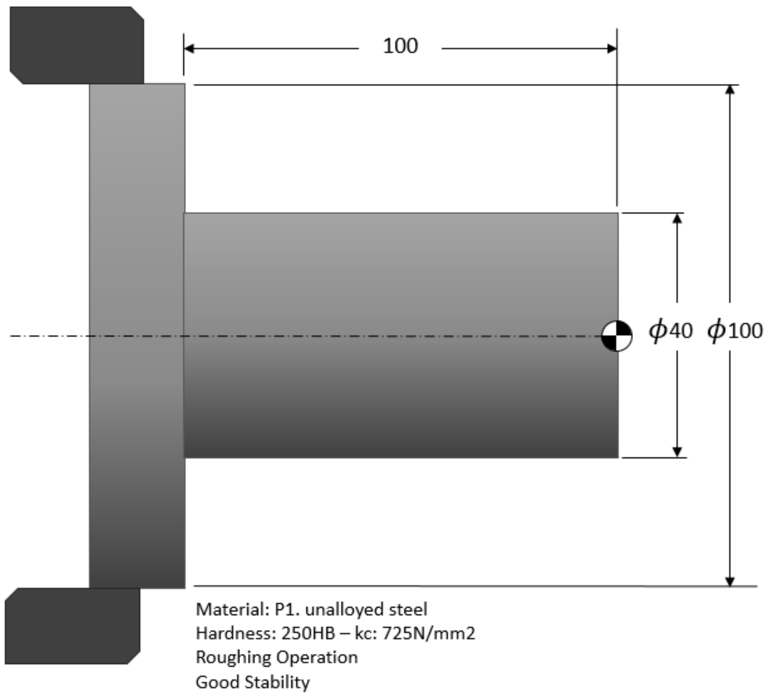

Figure 5.3 Heavy roughing operation example

The Table 5-4 introduces the working specifications for this roughing operation. It sets an initial and final diameter to 100 mm and 40 mm respectively, which defines a total depth turning of 30 mm, additionally, the total machining length is set to 100 mm. This geometrical information for this example is presented by the Figure 5.3.

The workpiece material is an unalloyed steel of 250HB and a specific cutting force of 600N/mm^2. Moreover, for this operation the stability condition is set as ‘Good’.

The machine specifications define a small lathe with a total power available of 10 kW and maximum speed spindle of 3000 rpm.

The equation (5-2) sets the fitness function for this operation. The machining time has been weighted 10 times, while the power consumption 0.5. In such way, that fitness function establishes that the solution must prioritize the machining time instead of the power consumption.

Table 5-5 Results for the heavy roughing operation example

Features	GA Results	Closer insert
ICmm	15.87	12.07
LEmm	21.2	11.7
REmm	0.609	1.19
WEP	false	false
Smm	5.56	4.76
AN	7°	7°
Angle	90°	90°
GRADE	4325	4325
Cutting parameters		
Closer Insert	CCMT 12 04 12-PR 4325	
Number of passes	6	
Depth of cut	5 mm	
Feed Rate	0.325 mm/r	
Cutting velocity	261 m/min	

The Table 5-5 shows the results for the GA evolution. This result are the reached features for the GA algorithm next to the closer tool-insert in the dataset. This table also presents the suggested tool-insert and its cutting parameters for this operation. Furthermore, At the Table 5-6 is introduced the evaluation for the goal variables which define the performance for the reached tool-insert.

Table 5-6 Goal variables evaluation for heavy roughing operation example

Goal variable	Variable	Equation.	Evaluation
Power Consumption	P	(4-4)	5.13 kW
Total Power Consumption	$passes \times P$	(4-4)	30.83 kW
Machining Time	T_m	(4-7)	1.84 min
Euclidean distance	$d_{euclidean}$	(4-12)	4.7830.
Speed spindle	HB	(4-8)	2080 rpm
High machining condition	MC_H	---	40
High machining condition	MC_L	---	10
Fitness Function	$fitness$	(5-2)	86.261

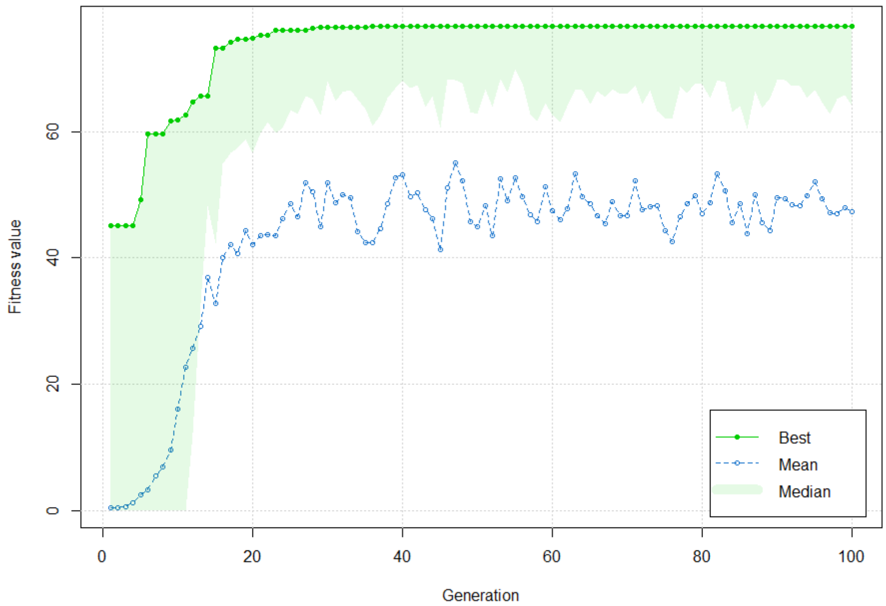

Figure 5.4 GA performance for heavy roughing operation example

5.3. Finishing operation

Finishing operations differs from roughing operation mainly in the fitness function definition. For this operations the stability and surface roughness performance define the tool-insert solution. The stability features must be defined in such way that the selected grade belongs the lower ISO area application related to wear resistance performance. This area application is addressed to finishing operations. Furthermore, the surface roughness performance must be lower than the maximum roughness defined by the working specification for the process.

Table 5-7 Working specifications for finishing operation example

Material specifications		
Final Diameter	D_i	40 mm
Machining Length	D_f	50 mm
Hardness	L_m	180 HB
Specific Cutting Force	HB	600 N/mm^2
Max. surface roughness	$R_{a\_\max}$	3 μm
Machine specifications		
Main Motor Power	P_{net}	15 kW
Maximum Spindle speed	$n_{\max}$	6000 rpm
General conditions		
Machine Operation	$CTPT$	Finishing
Stability	----	Good
Toot Life	T_{life}	15 min
Threshold Distance	Th_d	20
range ap_rec	ap_rec	0.01 – 5 mm

$$fitness = \frac{R_{a\_\max}}{R_a} + \frac{Th_d}{d_{eucliden}} + \frac{100}{MC\_H - MC\_L} \tag{5-3}$$

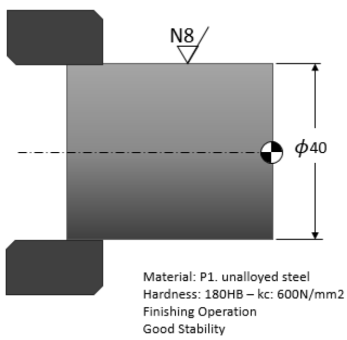

Figure 5.5 Finishing operation example

The Table 5-7 introduces the working specifications for this finishing operation. It sets a final diameter of 40 mm and a maximum surface roughness ISO N8. This surface specification defines a roughness of 3 μm. This geometrical information for this example is presented by the Figure 5.3 as well.

The workpiece material is an unalloyed steel of 180HB and a specific cutting force of 600N/mm^2. Moreover, for this operation the stability condition is set as 'Good'.

The machine specifications define a medium lathe with a total power available of 15 kW and maximum speed spindle of 6000 rpm.

The equation (5-3) sets the fitness function for this operation. This function evaluates the goal functions relate to surface roughness and stability grade, which were introduced in the section 4.3 Fitness function definition.

Table 5-8 Results for the finishing operation example

Features	**GA Results**	**Closer insert**
ICmm	5.55	6.35
LEmm	5.65	9.87
REmm	0.99	1.19
WEP	false	false
Smm	1.98	3.18
AN	5°	5°
Angle	35°	35°
GRADE	4325	4325
Cutting parameters		
Closer Insert	VBMT 11 03 12-PF 4325	
Depth of cut	0.3 mm	
Feed Rate	0.14 mm/r	
Cutting velocity	434 m/min	

The Table 5-5 shows the results for the GA evolution. This result are the reached features for the GA algorithm next to the closer tool-insert in the dataset. The information related to the suggested tool-insert is also presented. The reached tool was VBMT 11 03 12-PF 4325.

On the other hand, the Table 5-6 introduces the evaluation for the goal variables which define the performance for the suggested tool-insert.

Table 5-9 Goal variables evaluation finishing operation example

Goal Variable	**Variable**	**Equation.**	**Evaluation**
Power Consumption	P	(4-4)	0.189 kW
Machining Time	T_m	(4-7)	0.343 min
Euclidean distance	$d_{euclidean}$	(4-12)	6.48
Speed spindle	n	(4-8)	3456 rpm
Surface roughness	R_a	(4-10)	2.22
High machining condition	MC_H	---	40
High machining condition	MC_L	---	10
Fitness Function	$fitness$	(5-3)	48.33

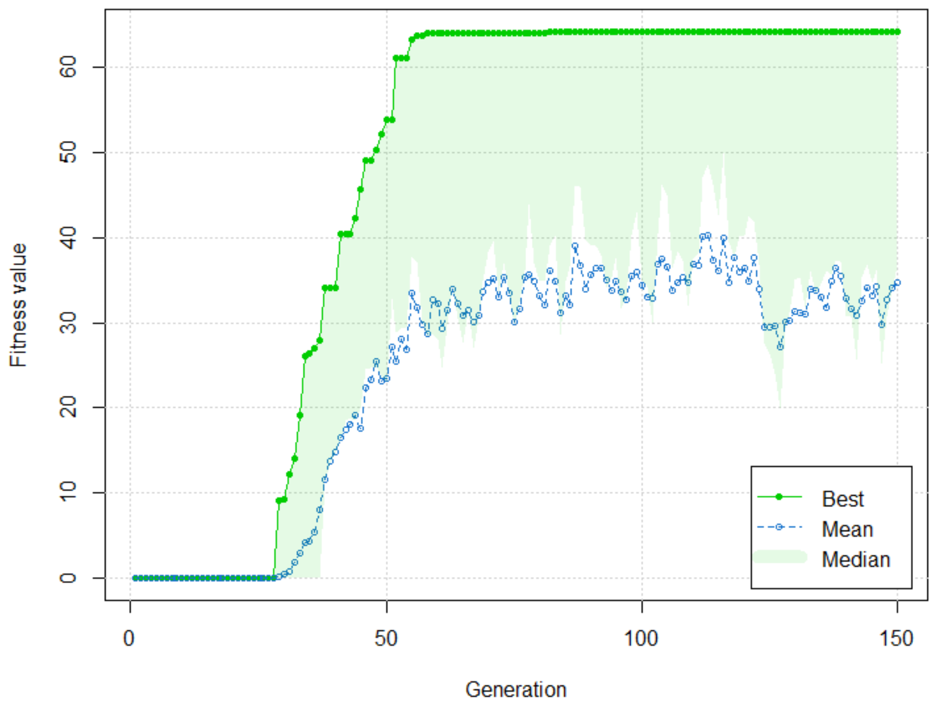

Figure 5.6 GA performance for finishing operation example

Chapter 6 Conclusions

An expert model for selecting cutting inserts and cutting parameters was designed for rough and finishing operations. These approach is addressed to turning operations only, but its application can be varied. This research uses the information from a tool supplier to embed knowledge in a useful expert system.

The proposed expert system model is based on artificial neural networks (ANN) and genetic algorithm (GA) which represent the modeling and optimization part for this research.

For the modeling, two artificial neural networks are implemented which infer feed rate and cutting velocity parameters. The feed rate model is defined as a function of insert features and a set depth of cut. The insert features represent macro-geometries of a tool-insert, i.e. cutting length, thickness, nose angle, nose radius, size, grade, etc. For the cutting velocity model, the inputs are the material specifications and a set feed rate. The material specifications are defined as inherent features of a working material for turning process, i.e. hardness, specific cutting force, ISO material group.

For the neural network validation an error comparison based on density functions is implemented. That approach proposes an alternative solution for the error validation for regression models based on recommended data by a supplier.

In order to evaluate some architectures for the ANN models, a heuristic search based on genetic algorithm is used. This approach evaluates the possible architectures and evolve them toward the most feasible one.

For proposed research in hereto, it was also introduced a heuristic search for a feasible tool-insert based on its characteristic into a certain environment. The algorithm used for this search was a genetic algorithm.

The introduced genetic algorithm optimization searches an optimal tool-insert which faces with a working specification and evaluates an acceptable performance given by a custom objective function. This objective function evaluates the performance under certain working conditions, for instance, the lowest power consumption, the shortest machining time and an acceptable surface roughness.

In such a way, this research presents a model to simulate knowledge and expertise which is embedding the information from a tool supplier. It returns, as result, a suitable insert-tool which is the most suited given certain working conditions previously defined. This research does not use a lookup table approach in the database, instead, it models the mechanical relations between the geometrical features of an insert-tool and its recommended cutting parameters. This expert system is able to embed the data from other models, different tool suppliers, previous machining works, and machine-shop workers expertise. Thus, this approach is not a fixed model and it can be adapted to whatever changing environment.

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