Politecnico di Torino
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Master of Science in Mechatronics Engineering

Master Thesis

End-effector tools wear prediction: machine and interaction modeling, system identification based on the EKF approach

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Abstract

This thesis work is part of the project MOREPRO, an industrial program owned by Brain Technologies, whose main goal is the realisation of a predictive monitoring system for the tool's wear and for the state of health of the machinery in real-time. The whole project is carried out in teamwork; in particular, the team's partition is the following:

- modelling team
- prediction team
- requirements team.

My initial role was within the modelling team with the aim of finding a kinematic and dynamic model of the system and create a simulation environment for the robot considered. Afterwards, I continued the modelling work for the prediction team in order to find a model for the interaction between the end-effector of the machine and the workpiece. The crucial parameter considered in the interaction model is the friction coefficient because it has a strong impact on the tool's wear. Different models of friction coefficient were studied and once found the final interaction formulation, this is added to the CNC machine model previously carried out by the prediction team, in order to achieve a better degree of accuracy and detail of the system.
During this work, I also had the opportunity to become more familiar with state observers, because an Extended Kalman Filter is used in order to perform the system identification, able to estimate the unknown parameters.
The whole work performed can be divided as follow:

- machine modeling from a Kinematics point of view;
- study and implementation of the interaction between the end-effector and the workpiece;
- system identification solution using an Extended Kalman Filter approach for parameters estimation.

The whole project was developed and implemented on Mathworks environment, both Matlab and Simulink have been employed.

Acknowledgements

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Contents

References **75**

List of Figures

List of Tables

1 Introduction

1.1 Industy 4.0

In the last years, the concept of 'Industry 4.0' has been developed inside the companies. This new idea, implies the use of new technologies that were not exploited before, in order to improve the working conditions, increase the productivity and the quality of the companies facilities. The three most important pillars of the 'industry 4.0' are:

- Smart production: collaboration between man and machines;
- Smart service: IT infrastructures that allow systems to be integrated;
- Smart energy: to always pay attention to energy waste.

Among the most used new technologies that allow to insert a company inside the context of I4.0, there are:

- Additive manufacturing;
- Advanced manufacturing;
- Augmented reality;
- Industrial internet;
- Cloud.

1.2 MOREPRO project goal

The MOREPRO project fits inside the context of 'Industry 4.0',with the aim of improving the performance of the production systems and decreasing the cost of maintenance, especially in the field of mechanical machining with high precision.

The main goal of MOREPRO project is to implement an innovative real time monitoring system able to control the state of health of the machine and the tool usury, in complex mechanical processing (precision mechanics), like metal cutting.
Precision mechanics, as the word itself says, includes all those material processing techniques, which require an high degree of attention and accuracy. Among these metal cutting methods there are metal turning and milling, and commonly both exploiting CNC machines. Normally, the processing begins with huge pieces of material, which are given shapes by chip removal; it is very important in that kind of working to have the best performance of the machine in order to have no production errors and a fairly high accuracy of the final product.

1.2.1 Functionalities

The main functionalities that MOREPRO project wants to reach are:

1. Monitoring of the state of health of the critical component of the machine; the idea is to use the sensors already present, and combine the data coming from these, with techniques like data mining, in order to have information about the state of health and degradation of the machinery.

2. Monitoring of the end-effector usury using digital-twin tools. The idea is to compare the values of the signals coming from the sensors with estimated quantities using different model of the system, in a virtual environment. The alert information comes from different values of current and power required, due to the wear of the tool.

3. Predictive models in order to estimate the residual life of the tools. The intention is to carry out a preventive maintenance in order to don't allow the line to be blocked for any faults.

The benefit is related with the improvement of the production system due to the prediction of the state of health of machines and usury of the tools. Being able to predict these conditions prevents blockages of production lines and might lead to an increase in efficiency of the production about the 20%.

1.2.2 State of Art

The available technologies on the market in order to achieve the goal of MOREPRO, have several limitations that do not allow to carry out the objectives previously mentioned in a precise manner.
The control of the tool's state is still an open problem and are not available many technique that allow to understand the conditions of the components of the machine, since it is difficult to split the usury effect signals from other factors. In fact, the acquired signals from the machine during the work, for wear observation, are strongly related with the instantaneous working conditions and also influenced by internal and external noise. Moreover, all these signals are strictly related with the chosen processing parameters. Normally, the average tool life considered is the one indicated on the data sheet of the used tool.
Below are presented two of the most used approaches for wear detection:

- System based on a threshold. This approach is not very precise and allow to detect only macro-irregularities, for example the component breakdown. In this way it is not possible to monitor and have information about less critical events, like tool usury. The biggest drawback is the presence of the false alarms due to the lack of processing of different signals and the consideration of a single threshold.
- System based on the evaluation of the signal coming from cyclical operations. This idea is more precise but is useful only when the same processing and

the same parameters are used. This is not common for the metal cutting operations and so it is not convenient to apply this method.

With both these techniques it is not possible to increase the productivity and avoid blockage of the machines. Following two innovative approaches are presented.

All the modern monitoring system, exploit Internet of things (IoT) techniques; this approach is related with all the physical objects, which are provided with sensors and can exchange data with other devices using an internet connection. The main problem with these methodologies is that the monitoring action and the predictive techniques depend on the working conditions of the machine. This means that for each change of the working condition, also the predictive algorithm must be changed and so it is not possible to define this method as 'standard' and applicable for many process. The second limitation of these approach is related with the computational point of view, due to the big amount of data that is possible to acquire and transmit.

In the last year more innovative direct and indirect (which expects the use of sensors) solutions have been tested, that foresee the use of neural network, machine learning and 'deep learning'. A good approach could be the one mentioned in [**?**], where the tool wear condition is based on Convolutional Neural Network (CNN).

Convolutional neural network, can be used as an automatic detection method for tool's wear, based on image acquisition. The main advantage of this approach is that the measurement can be done during the machining procedure. Differently from the other methods, here both the tool's wear and a quantitative study of the usury on each tooth of the tool are carried out. This method see the application of a sensor for the images acquisition that is directly placed inside the CNC machine, and the acquired images are processed in order to understand the level of usury. The resulting pictures from this processing are used in order to training and test the network model. Furthermore, a Robert operator is used in order to locate wear boundary, trimming the edges of the image. Different tests and experiments show how this method is reliable and accurate in finding the features.

Both IoT and CNN approach have some limitations due to the huge amount of data to be treated. A possible solution to this limitations is to use an approach of distributed intelligence architecture, called Edge computing approach, that reduce the required computation because in this way the acquired data are pre-elaborated at the component level and sent to the global net later. The idea is to combine signals coming from different sensors, elaborate this information and identify the state of decay of the components.

1.2.3 Innovations of the project

The main idea of the project is to built a distributed intelligence architecture, in order to control and monitor the machines and their components. The different levels of this acquisition system allow to :

- use the already present sensors and acquired data, in order to process them directly on site, through edge device approach;
- use the previous elaborated data to implement some algorithms, called learning algorithm, that are able to predict the state of health of the machine.
- Thanks to the previous steps, it is now possible to exploit the obtained data in order to apply predictive maintenance procedures. In this way it is possible to prevent severe damage to the machinery and improve the production system.

1.2.4 Edge computing approach

One of the most common approach to deal with the problem of wear's prediction and state of health of the machines is to use IoT techniques. One of the main problem of the IoT techniques in this field is due to the big amount of data to be acquired and analyzed, which signify long processing times.

A feasible technique to avoid this problem is an edge computing approach figure(1); in this method the computations are performed at the edge of the network and this means that the data are analysed and elaborated near the place where they are generated, ensuring shorter latency times and avoiding a large data transfer. This is possible due to some devices called "Edge devices" directly implemented on the machines, that send to the cloud only the useful data and not raw one.

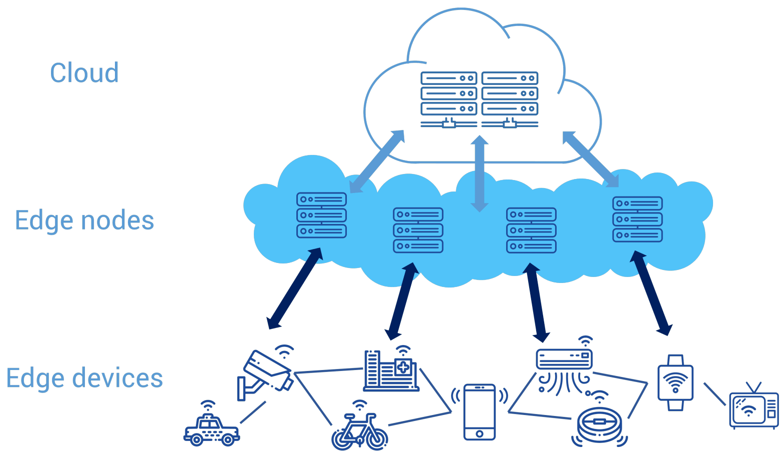


Figure 1: Edge computing hierarchy.

1.3 Partnership

The MOREPRO project involves different companies in his development. Each companies has a different role in the project and different skills that can be used in order to achieve a good solution for the predictive monitoring system. Below a list of the participating companies is exposed.

- Brain Technologies:provides engineering and scientific services for industrial projects and is the project manager during the development of the MOREPRO project. The main role of the company is the design of the predictive system and of the edge-computing device.It is also involved in the implementation and validation of the final prototype on the production line.
- Machining Centers Manufacturing S.p.A.: is involved in the definition of the requirements and constraints of the algorithm. Its main role is the acquisition of the data from the machines, support for the installation of the MOREPRO solutions on the machines of CAMS and for last, test and validation of the developed algorithm.
- AL.MEC: is a company of mechatronic components. In MOREPRO, its main role is to design and produce electronic boards able to collect data from the sensors and their subsequent processing.
- CAMAS: is a company for the high precision machining. It is involved in the definition of requirements for the predictive monitoring system, definition of the use case and implementation test and validation of the monitoring system on the production line.

1.4 Team organization

The MOREPRO project is carried out by a team of six mechatronics master's student supervised by Brain Technologies' engineer and professor of the Department of Control and Computer Engineering (DAUIN) of Politecnico di Torino. ?The beginning of this thesis work was also the starting point for MOREPRO project, after a first explanation about the goal of the project and the first ideas in order to carry out a first implementation, a subdivision in teams is necessary.

The whole work is organised following a V-model that is a development model where all the phases of the process are related by the cycle shown in figure(2). This procedure allows a good efficiency and organization of the work to carry out.

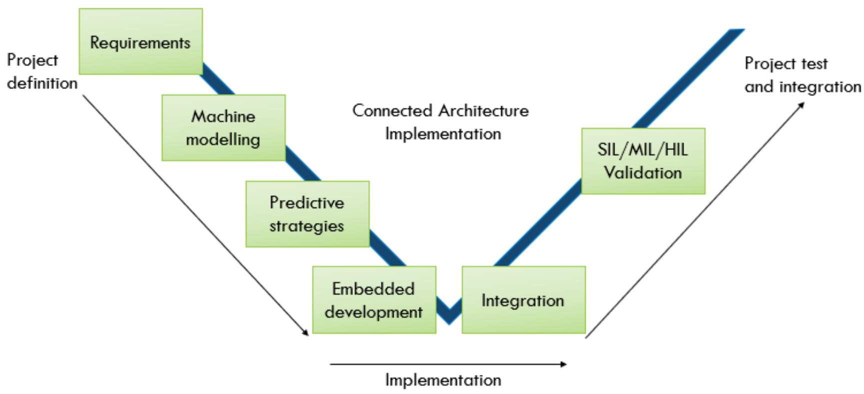


Figure 2: V-model for the project development

The teams subdivision, shown figure(3), is the following:

- Modelling team: the main goal of this team is firstly to create a complete model of the machine from a kinematics and dynamics point of view and also to create an animation able to simulate the movements of the machine in a virtual space. Afterwards the aim is to model the interaction between the tool of the machine and the workpiece, in order to add more details to the CNC machine model created by the prediction team.
- Prediction team: this team performs the core of the MOREPRO project; in fact the main objective is to create an algorithm able to perform a predictive analysis and also the parameter estimation of the considered system . The first task carried out is the development of a first simple model of the machine. Then in order to achieve the main goal, a multi-model approach is implemented in order to execute the wear and state of health estimation.

- Requirements team: the goal of this team is to analyze the requirements and specification of the project having an overall view of the whole. Another task is that in order to perform some tests of the implementation, a design of experiment is carried out by the member of this team.

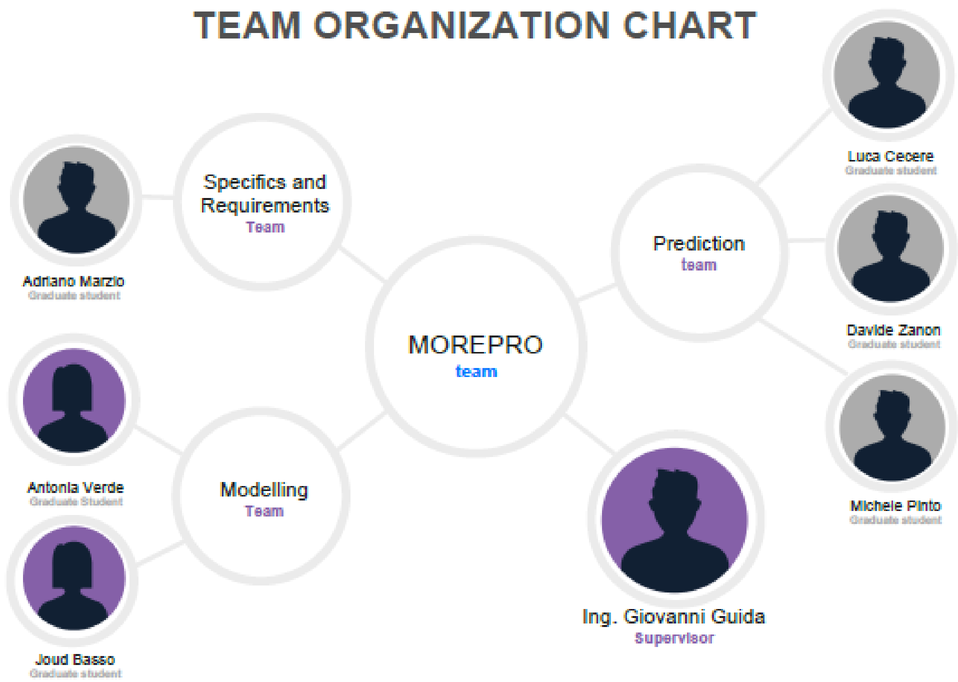


Figure 3: MOREPRO team organization

The initial division in teams was not respected for the whole period of the thesis work; after the first months some of the members of the teams started individual work while others carried out new tasks while still in the team. Although the subdivision of the team was strict, the information shared and the support was very important for a personal growing and for the progress of the project.

1.4.1 Step to follow

The idea is to create a module for the prediction algorithm that processes the real signals coming from the considered system (that in our case is the CNC machine) and compare them with the output coming from the process simulation (based on a simplified model of the system), in order to produce an estimate of the state of health and tool wear. These algorithms can be performed directly at the edge device level in real-time. The main steps to follow are the following:

1. To build a model that is a detailed representation of the real considered system (plant). Inside this model the general equations of the CNC-machine are implemented in order to simulate the whole structure. Different models are implemented, increasing step by step the complexity in order to add more details and to have a model as close as possible to the real one.

2. To build an Extended Kalman Filter Block. This block is composed by n-models that consider different values of some parameters and for this reason produce each one a different output. The output of these models is compared with the output of the plant (that represent the real system) and analysing the error coming from this process it is possible to estimate the value of the parameters inside the plant and predict the tool wear state.

3. Using some system identification methods, in order to estimate the possible range of values of the unknown parameters for replacing the correct values inside the model.

1.4.2 Objective of the thesis

The whole thesis work revolves around the modelling of the system from different points of view. Modelling is a very important starting point for each project and allows to simplify and better understand the considered structure.

The first model studied and performed is the kinematic model of the CNC machine used to implement a 3D animation of the system.

The second important step is to find a model for the interaction between the end-effector of the machine and the workpiece to model. This is performed studying many models that are present in the literature, choosing and joining only the most performing formulations.

The last part of the work foresees the estimation of the unknown parameters of the system performing the system identification with the implementation of an Extended Kalman Filter.

2 CNC machine and modelling

As mentioned above the whole MOREPRO project turns around the predictive monitoring of the tool's wear and state of health of the machine considered that in our case is a five-axis CNC machine. This kind of machinery is widely used because of his efficiency and quality for processing complex 3D surfaces [2].

2.1 Why modelling is important

A huge amount of work of the thesis is based on modelling. In the first part a kinematic model of the machine is performed and later the interaction is studied.
The model of a system, in most cases, is an essential part of the work and is done in order to conceptualize it, make the structure easier to understand, visualize and simulate; in fact they create experimental conditions able to reproduce the behaviour of the system under certain specifications. To do this only the key aspects must be treated, at least at the beginning and later step by step the model can be complicated adding more details and information that let the outputs to be closer possible to the real situation. In our days is very important to create a simulation environment because allows to reduce the coasts, decrease the amount of material used for tests and do not favor the use of the machinery for reasons other than processing.

2.2 CNC machine

The tool's wear and the machinery state of health are both essential parameters to monitor talking about CNC machine used for particular mechanical processes that require an high degree of accuracy for the production of the final piece.
The whole MOPREPRO project, foresees its initial design, applied to a CNC machine used for milling operations.
In the following paragraph there is a presentation of the most important features of

a CNC machine and of the kind of processing able to provide. Afterwards, in the next chapters, a kinematic model is found and also the starting model adopted to synthesize the physical characteristics of the processing is presented. In the end, a more detailed model, due to the addition of the information about the interaction between the end-effector and the material to work is analyzed.

2.2.1 CNC machine features

Nowadays the processes in the companies are increasingly automated, indeed the working are not performed anymore only by humans and this is because machines have a superior accuracy compared with them and can perform working in less time. An automated system is composed by three main components [3] which are a power units, a control system and a program which contains the instructions that the machines has to follow.

A Numerical Control(NC) is a programmable automation techniques which provides the handling of the machine's tool, controlled by the program that contains the instructions related to the speeds and the relative positions between the end-effector and the workpiece. Several are the applications of the NC, most of them are related with machine tool operations such as milling, drilling and turning but also other kind of implementations are useful, for example rapid prototyping and assembly. For this reason the program which control the machine can be always changed related with the process that should be performed.
The main units of a NC system are shown in figure(4):

- Program: is the code which contains the instructions for the process, especially information about the relative position between the end-effector and the piece; for this reason a base reference frame must be specified. The axes to consider are six:

- three for linear movements: x,y,z. Usually x and y control the position of the tool on the plane while the z coordinate is used for the vertical situation.

  Inside the code a sequence of x-y is specified.

- three for the orientation: a,b,c.

- Machine control unit: it is a micro computer which reads the instructions contained in the program and let the machine to perform the movements, transforming the command into mechanical actions.

- Processing equipment: it is the machine itself where the main components are the motors, tool and the worktable.

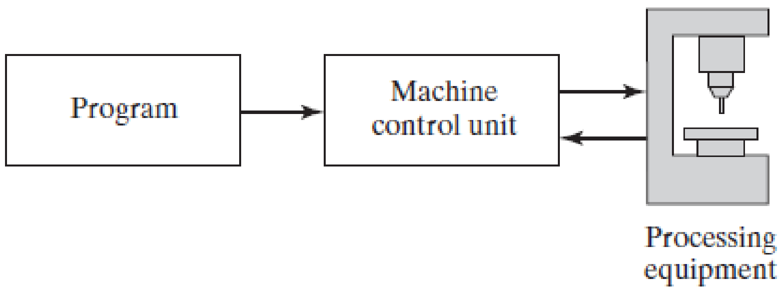


Figure 4: NC system structure

The difference between an NC and a CNC(computer numerical control) systems is only related with the machine control unit that in case of a CNC machine is a computer composed by a central process unit, memory, I/O interface and the control for the machine.

2.2.2 Main application of CNC

As previously said, the applications of the CNC are several. Most of them are related with machine tool processes like metalworking; this processes foresees that the final workpiece's shape is achieved by chip removal, starting from a larger piece of material, in order to join some specifications. This technique is versatile because different materials, shapes, processes and surfaces can be provide.

The processes related with metalworking are turning, drilling, milling and grinding, where each process expects different cutting condition (speeds, depth of cut, feed) and different tools, shown in figure(5).

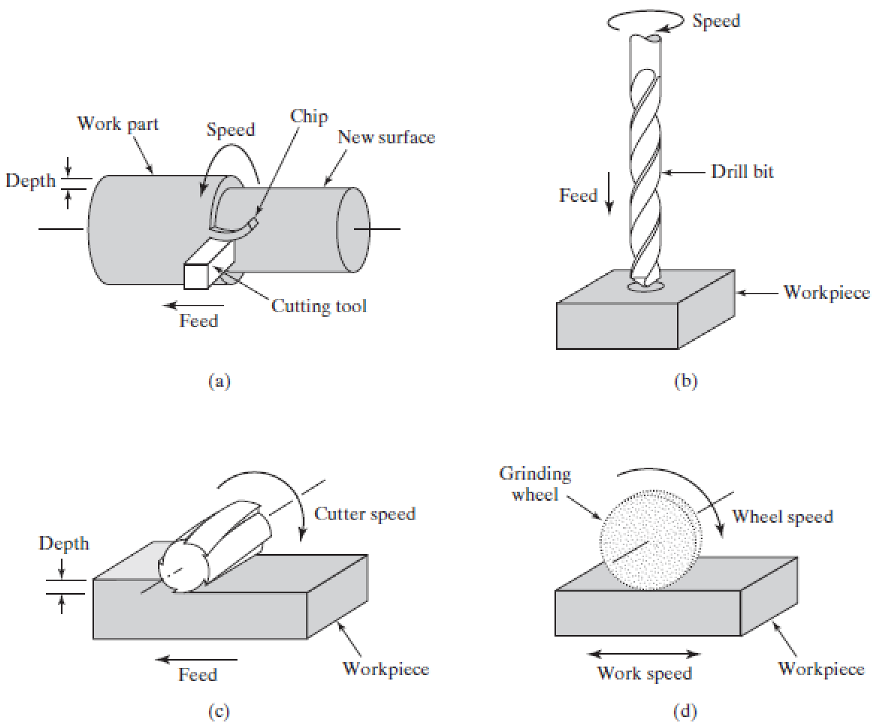


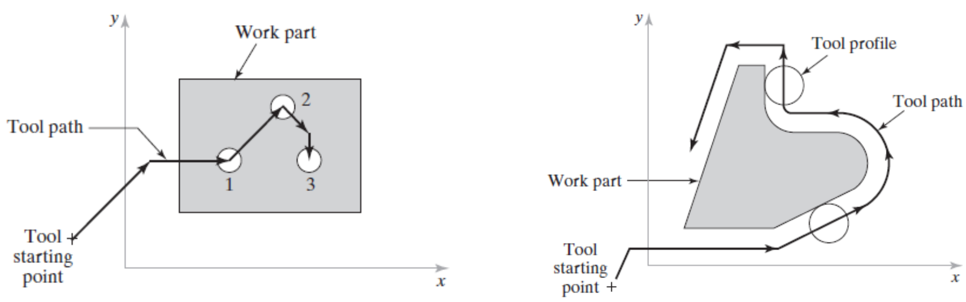
Figure 5: machining processes: (a) turning, (b) drilling, (c) peripheral milling, and (d) surface grinding.

Considering the milling process, there are two parameters to consider: the cutting speed which is the relative velocity between the cutter and the workpiece (m/min); usually this is expressed as function of the spindle speed (rev/min). The other parameter is the feed or chip load, which refers to the size of the chips removed by each tooth

2.2.3 Motion Control

The motion control of the machine's tool is done by the control unit and is related with the process to perform; two different kind of motion can be implemented figure(6):

- Discrete motion: it is used for drilling operations. The end-effector moves from one point to an other one and performs the process only when specific positions are reached.
- Continuous motion: this kind of motion is used for milling. The whole process is performed while the tool follows a certain controlled trajectory. With this application complicated geometries can be achieved.



(a) Point to point motion (b) Continuous motion

Figure 6: Motion control of a CNC machine

2.2.4 CNC softwares

As previously mentioned the cutter in order to shape the material follows the program's instructions. The first step to follow is to use a CAD program in order to draw the final frame of the material that you want to generate. Secondly the CAD drawing is transformed, using CAM software, into possible tool trajectories, associating to the CAD drawing some coordinates. The CNC software is, in the end, used in order to pilot the tool in order to follow the process.

The CNC control, takes information from the encoder present on the axes of the machine, able to give news about the actual position, and takes the instructions from the program where the process is described in order to move the end-effector along the trajectory pre-established.

2.2.5 Advantages and disadvantages of CNC machine

The benefits of using these machines are considerable, they allow to carry out very precise work in a very short time and with moderate costs.
The production is more precise than the manual one and it is due to the high number of degrees of freedom, depending on the number of axes of the machine. Whit this techniques it is possible to produce very complex geometries, difficult to achieve with the traditional methods. The application of CNC method is also useful in order to reduce the skills required to a worker. The main drawback is related with the high costs of the machine due to the electronics, control unit and hardware but also due to the maintenance actions to perform in order to have always the maximum performance of the machine.

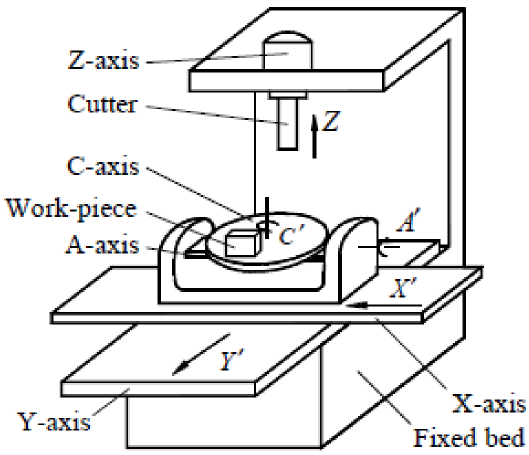


Figure 7: A five-axes milling machine.

The milling machine considered in MOREPRO project, has 5 axes of motion; this means that the possible movements are along X,Y,Z axes to which is added the inclination and the rotation of the spindle.

3 Kinematic model of a CNC machine

Modelling is a very important and necessary step in robotics; the obtained mathematical model is used in order to perform some simulations that can allow to better understand the robot movements and behaviours. The most important benefit in modelling and simulate a system is that using environment of simulation, like MathWorks (MATLAB, Simulink) is less expensive than performing real test with the system and helps also to collect the data. The initial models, normally, are as simple as possible in order to explain the main characteristics of the system. But in order to have good information from the simulations performed,it is better to create a model close enough to reality and for this reason to increase the level of details and accuracy of the model.

3.1 Kinematic model

In the following paragraphs, a generalised kinematic model is developed. The kinematic model is used in order to implement movement control strategies and deal with the description of the motion without considering dynamics components (like force and torque).

Before starting, some premises must be made in order to explain some basic concept. A common manipulator, robot, or in our case a CNC machine, can be easily and schematically represented as a succession of links, which represent the arms of the robot, connected between them with joints which are the actuators of each arm. The succession of links and joints constitutes what is called Kinematic chain. There are two kinds of joint:

- prismatic: allows a translation or a linear sliding movement between links;
- revolute: constrains the motion of two bodies to pure rotation along a common

axis. Unlike the prismatic, this joint does not allow translation, or sliding linear motion.

Moreover, inside the kinematic chain can be distinguished other two important components, which are the end-effector and the base. The base is fixed and is the platform to which is bonded the first link, while the end-effector is attached to the last link of the chain and is the interface that allows the robot to compute different tasks. The position, the orientation and in general, the movement of the robot are expressed with respect to a frame attached to the base, that is considered a fixed reference frame.
For what concern the robotic field the kinematics has the following classes:

- Kinematics: allows to find the relationship between the position and the orientation (pose) of the end-effector of the robot and the joints.
- Differential Kinematics: helps to find the link between the joints and end-effector velocities. In order to achieve this result the use of a mathematical operator is needed, the Jacobian.
  Another treated difference is the following:
- Direct Kinematics (DK): the goal of the DK is to describe the end-effector motion as function of the joints' coordinates, using linear algebra tools.
- Inverse Kinematics (IK): the aim of the IK is to find the joints' coordinates starting from the motion of the end-effector into the operational space.

The first step to follow in order to perform a control of a robot is to create a kinematic model of the system.

3.2 Direct kinematics

As mentioned above, the aim of the direct kinematics is to find the end-effector position and orientation as function of the joint's coordinates and for this reason it is important to express the pose of the tool with respect to a base reference frame connected to the base (O_b: base frame), figure(8).

The problem of the direct kinematic can be solved in different ways.

One approach is related to the geometrical structure and plans to find the end-effector pose using an homogeneous transformation matrix (HT) as function of the joint coordinates (q).

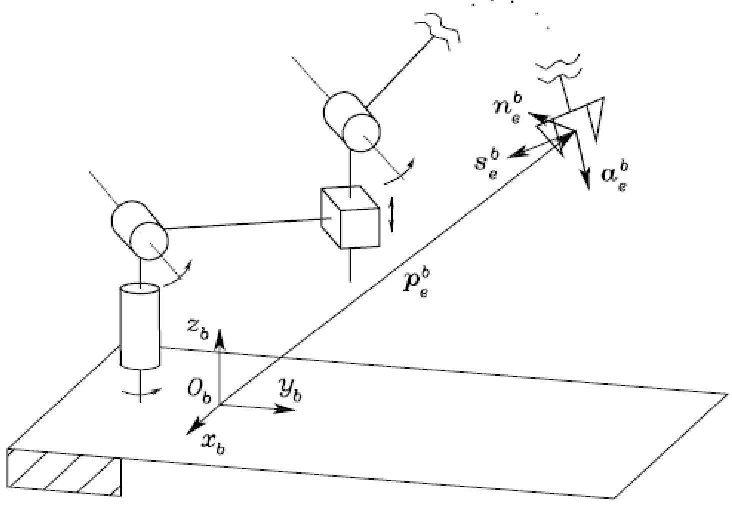


Figure 8: Kinematic chain for end-effector pose detection

The HT is composed by a translation vector (p_e^b) of size [3*1] and a [3*3] rotation matrix which expresses the rotation between the end-effector frame (O_e) and the base frame (O_b).

$$\boldsymbol{T}_e^b(\boldsymbol{q}) = \begin{bmatrix} \boldsymbol{n}_e^b(\boldsymbol{q}) & \boldsymbol{s}_e^b(\boldsymbol{q}) & \boldsymbol{a}_e^b(\boldsymbol{q}) & \boldsymbol{p}_e^b(\boldsymbol{q}) \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

The second possible method for finding the direct kinematic of a manipulator is to use the Denavit-Hartenberg convention. This is a systematic way to find the final pose of the end-effector. It is used to tackle the study of DK in situations where applying the geometric approach is difficult due to the configuration. In this thesis work both methods are used and explained in the following paragraph.

3.2.1 Application of the Homogeneous transformation method

What is represented in figure(9) is the schematic representation of the CNC machine used in MOREPRO project. As can be seen, the five-axis CNC machine is composed by two different open kinematic chains, including in one side the cutter and on the other side the plate where the workpiece is positioned.

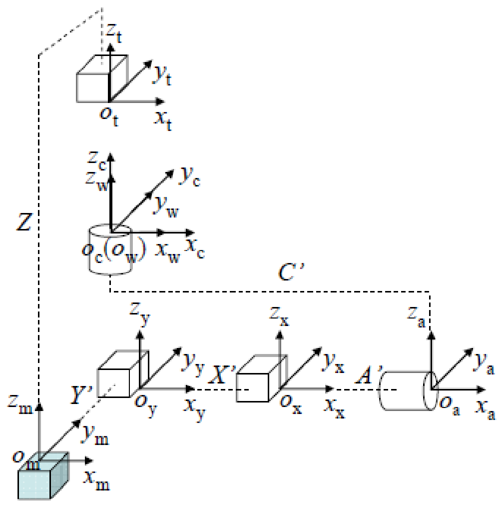


Figure 9: CNC machine chains.

What is modeled in the following thesis work, does not include the consideration of the open chain of the cutter, but a manipulator made up of 5 joints, in which the first three are prismatic and the last two are revolute. Moreover in dynamic and kinematic analysis, the last revolute joint is not considered (joint 5) because it is used for machining, which rotates at a certain speed to shape the material but does not perform any other type of movement and has no influence on kinematic and dynamics equations. In figure(10) there is the representation of the scheme adopted for the modelling.

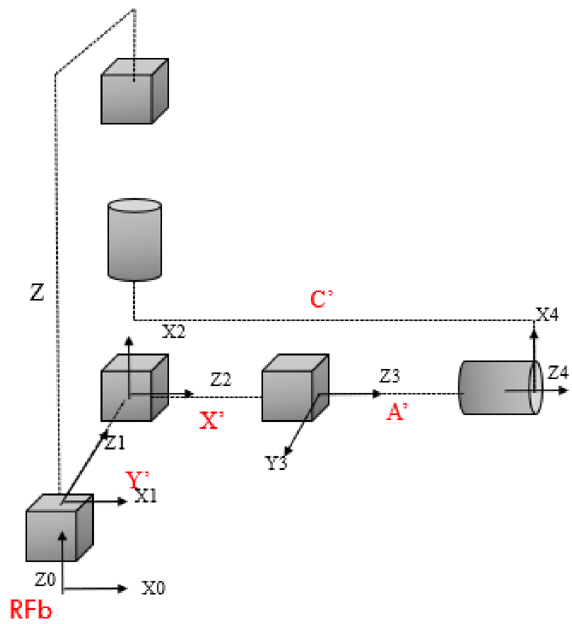


Figure 10: Considered model of the CNC machine

In order to compute the direct kinematic of the end-effector with the geometric approach, the homogeneous transformation matrices are calculated between each base frame and the base.

$$T_1^0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & -1 & 0 & a_1 + d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_2^0 = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & -1 & 0 & a_2 + d_2 \\ 1 & 0 & 0 & a_1 + d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_3^0 = \begin{bmatrix} 0 & 0 & 1 & a_3 + d_3 \\ 0 & -1 & 0 & a_2 + d_2 \\ 1 & 0 & 0 & a_1 + d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_4^0 = \begin{bmatrix} 0 & 0 & 1 & a_4 + a_3 + d_3 \\ sin\theta & -cos\theta & 0 & a_2 + d_2 \\ cos\theta & sin\theta & 0 & a_1 + d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

3.2.2 Denavit-Hartenberg convention

Another way in order to find the direct kinematics is to use the Denavit-Hartenberg convention (DH). Normally this convention is used for more complicated manipulator, like anthropomorphic one because the level of complexity of the structure is higher and finding the direct kinematic with the geometric approach is more difficult. This systematic approach helps to position the reference frame on each joint of the kinematic chain, and to find the relative pose between one joint and the other. As described in [4], the rule of the Denavit-Hartenberg convention, in order to find in the right way the reference frames, and looking at figure(11) are the following :

- Choose axis z_i along the axis of Joint i+1.
- Locate the origin O_i at the intersection of axis z_i with the common normal to axes z_{i-1} and z_i. Also, locate $O_{i'}$ at the intersection of the common normal with axis z_{i-1}.
- Choose axis x_i along the common normal to axes z_{i-1} and z_i with direction from Joint i to Joint i + 1.

- Choose axis y_i so as to complete a right-handed frame.

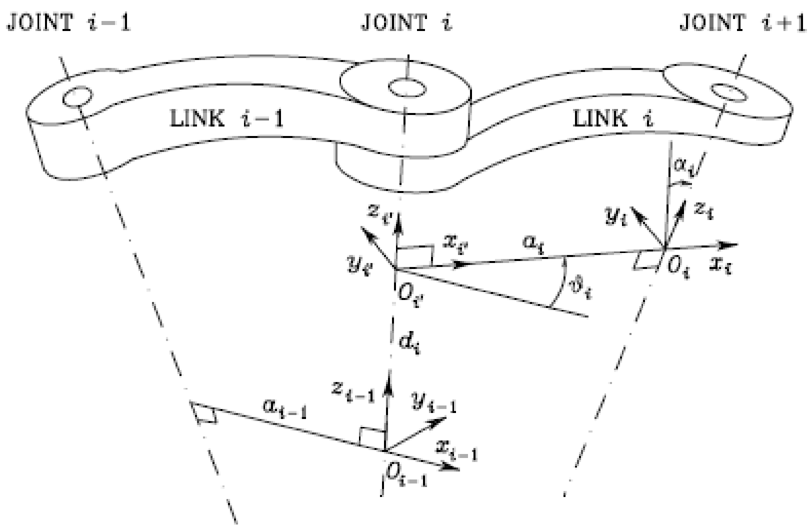


Figure 11: Denavit-Hartenberg convention

There are some situations in which it is not possible to uniquely choose the reference systems with the DH convention; for example for the first frame (RF_0), only the Z axis is chosen in the direction of motion of the next joint, but the X axis and the origin can be arbitrarily chosen. The same happens for the last joint (RF_n); since there is no the joint n+1, the direction of Z axis is not determined, and only the direction of x_n is along z_{n-1}. An indeterminacy is present also when the two consecutive axis are parallel, due to infinite common normal between them; while if two consecutive axes intersect, the direction of the X axis is indeterminate. The main parameters adopted to describe two consecutive RFs with the DH convention are the following:

a_i: is the distance between two origins O_i $O_{i'}$. This is a constant parameter and depends only on the geometry of the considered system.

d_i: is the distance between the two origins along z_{i1} In the case of the prismatic joint, d_i is the joint variable.

α_i:is the angle between z_{i1} and z_i along x_i, considered positive when rotation is counter-clockwise. Also α_i is a constant parameter that depends only on the geometry.

θ_i: is the angle between the axes x_{i1} and x_i along the axis z_{i1}. Applying this method to our configuration the DH parameters found are the shown in the table(1):

DH parameters	a_i	d_i	α_i	θ_i
joint$_1$	0	$a_1 + d_1$	-90°	0°
joint$_2$	0	$a_2 + d_2$	-90°	0°
joint$_3$	0	$a_3 + d_3$	0°	0°
joint$_4$	0	a_4	0°	t_4

Table 1: Denavit-Hartenberg parameters

The d_1, d_2, d_3 are the joint variables of the first three prismatic joints, while t_4 is the revolute joint's variable. Replacing the obtained parameters inside the following roto-translation matrix it is possible to find the HT between two consecutive reference frames.

$$\boldsymbol{A}_i^{i-1}(q_i) = \boldsymbol{A}_{i'}^{i-1}\boldsymbol{A}_i^{i'} = \begin{bmatrix} c_{\vartheta_i} & -s_{\vartheta_1}c_{\alpha_t} & s_{\vartheta_i}s_{\alpha_i} & a_i c_{\vartheta_i} \\ s_{\vartheta_i} & c_{\vartheta_i}c_{\alpha_i} & -c_{\vartheta_i}s_{\alpha_i} & a_i s_{\vartheta_i} \\ 0 & s_{\alpha_i} & c_{\alpha_i} & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Multiplying all the HT matrix, the direct kinematic is performed:

$$A_0^n(q) = A_1^0(q)A_2^1(q)A_3^2(q)$$

3.3 Differential kinematics

Differently from kinematics, the differential kinematics allows to find the relationship between the end-effector velocity, both linear and angular, as function of the joints velocities. The mathematical operator that allows to find this link is the Jacobian. In the following work, the used Jacobian is the Geometric one, but there is the possibility to find also an Anlitical Jacobian deriving the Direct Kinematics with respect to the joints variables.

Calling $\dot{p_e}$ the linear velocity of the end-effector and w_e the angular one and $\dot{q}$ the velocity at joint level, the following equations can be written:

$\dot{p_e} = J_p(q)\dot{q}$ and $w_e = J_o(q)\dot{q}$ to which follows: $V_e = [\dot{p_e} w_e]^T = J(q)\dot{q}$, called the differential kinematic equation of a manipulator.

The Geometric Jacobian can be written as: $J = [J_p J_0]^T$ and is a matrix of dimension (6xn), where n is the number of the joints in the considered configuration.

For what concerns the linear velocity:

$$\dot{p_e} = \sum_{i=1}^{n} \frac{\partial p_e}{\partial q_i}\dot{q}_i = \sum_{i=1}^{n} \jmath_{Pi}\dot{q}_i$$

J_{pi} takes into account the contribution of each joint on the linear velocity of the end-effector, when the other joints are blocked.

For a prismatic joint, where the joint's variable $q_i = d_i$, we can write:

$\dot{q}_i \jmath_{Pi} = \dot{d}_i z_{i-1}$

$J_{Pi} = z_{i-1}$

For a revolute joint, where the joint's variable $q_i = \theta_i$, we can write:

$\dot{q}_i \jmath_{Pi} = \omega_{i-1,i} \times r_{i-1,e} = \dot{\vartheta}_i z_{i-1} \times (p_e - p_{i-1})$

$J_{Pi} = z_{i-1} \times (p_e - p_{i-1})$

Considering the angular velocity of the end effector:

$$\omega_e = \omega_n = \sum_{i=1}^{n} \omega_{i-1,i} = \sum_{i=1}^{n} J_{Oi}\dot{q}_i$$

for a prismatic joint:

$$\dot{q}_i J_{Oi} = 0$$

$$J_{Oi} = 0$$

for a revolute joint:

$$\dot{q}_i \jmath_{Oi} = \dot{\vartheta}_i z_{i-1}$$

$$J_{Oi} = z_{i-1}$$

Putting all together, in the end the Geometric Jacobian can be written as:

$$\begin{bmatrix} J_{Pi} \\ J_{Oi} \end{bmatrix} = \begin{cases} \begin{bmatrix} z_{i-1} \\ 0 \end{bmatrix} & \text{for a prismatic joint} \\ \begin{bmatrix} z_{i-1} \times (p_e - p_{i-1}) \\ z_{i-1} \end{bmatrix} & \text{for a revolute joint.} \end{cases} \tag{4}$$

Where:

- z_{i-1}, are the first three elements of the third column of the homogenous transformation matrix A^0_{i-1}, in the case of $z_0 = [001]^T$;
- P_e, is a vector composed by the first three elements of the fourth column of the homogenous transformation matrix A^0_e, with $P_0 = [000]^T$;
- P_{i-1}, is the vector of the three elements of the forth column of the matrix A^0_{i-1}.

Starting from these considerations, the Geometric Jacobian for our configuration can be written as:

$$J = \begin{bmatrix} z_0 & z_1 & z_2 & z_3 x(P_e - P_3) \\ 0 & 0 & 0 & z_3 \end{bmatrix} \tag{5}$$

$$J = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

3.4 Application and Animation

The previous computation to find the direct kinematic and the Jacobian have been used in order to compute the Inverse Kinematics and to find the joint variables knowing a possible trajectory for the end-effector. There are different ways in order to invert the kinematics of a robot, the idea is to use the inverse differential kinematics (IDK) because this creates a linear mapping between the end-effector and the joints velocities. The inverse kinematics problem finds the solution for the determination of the joint velocities $\dot{q}(t)$ from the end-effector velocity $v_e(t)$. Starting from the formulation of the differential kinematics

$$v_e = J(q)\dot{q} \tag{7}$$

the inverse differential kinematic equation is the following:

$$\dot{q} = J^{-1}(q)v_e \tag{8}$$

The Jacobian must be square and full rank in order to be invertible. Starting from the joint velocity $\dot{q}$, also the joint variable q can be found by integrating the joint velocity and considering q(0) as known:

$$\boldsymbol{q}(t) = \int_0^t \dot{\boldsymbol{q}}(\varsigma)d\varsigma + \boldsymbol{q}(0) \tag{9}$$

In figure(12) the inverse kinematic algorithm is shown, implemented in the Simulink environment. The starting idea in order to build this scheme is to consider a difference between the actual position of the end-effector x_e and the desired position of x_d, obtaining the error e=x_d - x_e.

Deriving the last equation $\dot{e} = \dot{x_d} - \dot{x_e}$, where $\dot{x_e}$ is the velocity in the operational space (v_e), the last formulation can be rewritten as: $\dot{e} = \dot{x_d} - J(q)\dot{q}$. In order to perform the inversion of the kinematics, the Jacobian must be square and not singular, moreover, K must be a positive definite diagonal matrix:

$$\dot{q} = J^{-1}(q)(\dot{x_d} + Ke) \tag{10}$$

The eigenvalues of matrix K determine the speed with which the error will tend to zero during the trajectory, the higher the eigenvalues are faster the error will tend to zero. Inside the block scheme, inverse of the Jacobian is used in order to find $\dot{q}$, while the direct kinematic is computed in order to find the effective position of the end-effector from the joint variable q.

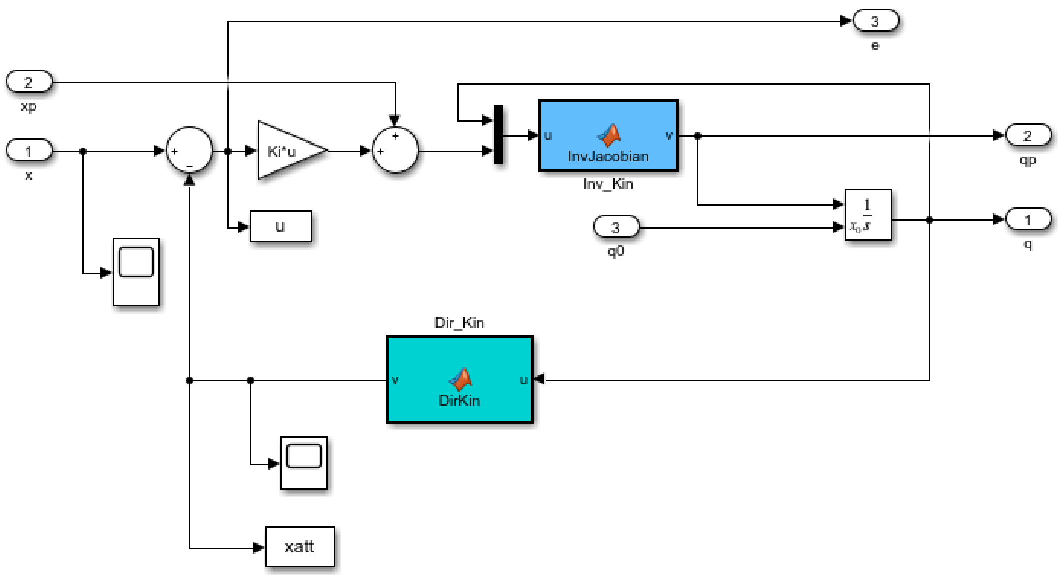


Figure 12: Inverse kinematics algorithm

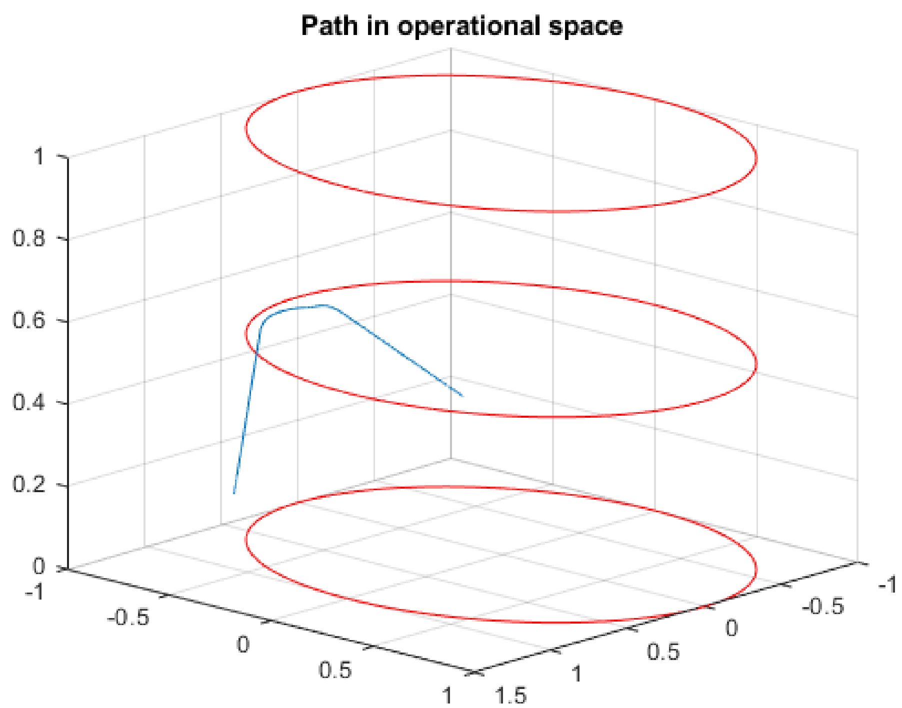


Figure 13: Path in operational space

The devised code starts from the definition of a path in the operational space, shown in figure(13), and it is built on the plane z=0 and then rotated with an homogeneous transformation matrix in order to have the path in the 3D space. The path is made by a sequence of four points p_1, p_2, p_3 and p_4 connected between them by segments. Moreover, the trajectories figure(14), velocities figure(15) and the accelerations figure(16)in the operational space were derived. The trajectories in the operational space are made starting from the path and adding timing law, specifying the speed that the end-effector should have or the acceleration.

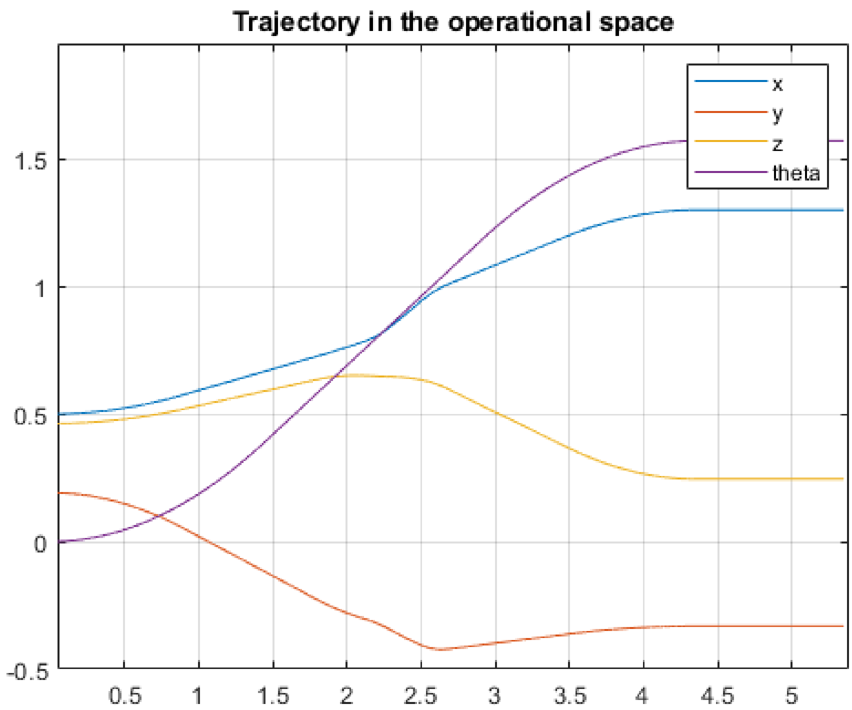


Figure 14: Trajectories in the operational space

The idea is to build trajectories in operational space because in this way the position and orientation of the end-effector are directly specified, while defining the trajectories in the joint space it is not easy to understand the behaviour and the motion of the manipulator. The only problem when defining the trajectories in the operational space is that the inverse kinematics should be applied in order to find the joint's variable.

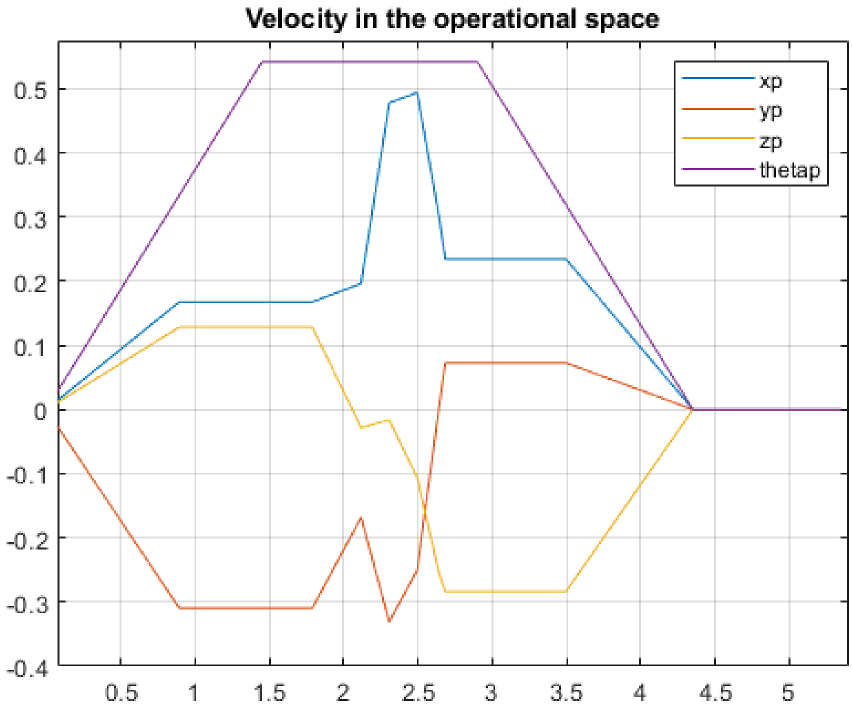


Figure 15: Velocities in the operational space

When only the initial and final position are specified for trajectory planning, there are infinite solutions in order to satisfy this requirement; the idea is to use a solution that is able to reduce the consumption of energy. The planning of trajectories in the code is generated using the function 'segment' in MATLAB. This function takes as input the initial and final points and the time in which the end-effector must travel the path. This method is characterized by an initial and final velocity equal to zero with a trapezoidal profile, the acceleration in the starting part of the path and the deceleration in the final part have the same length.

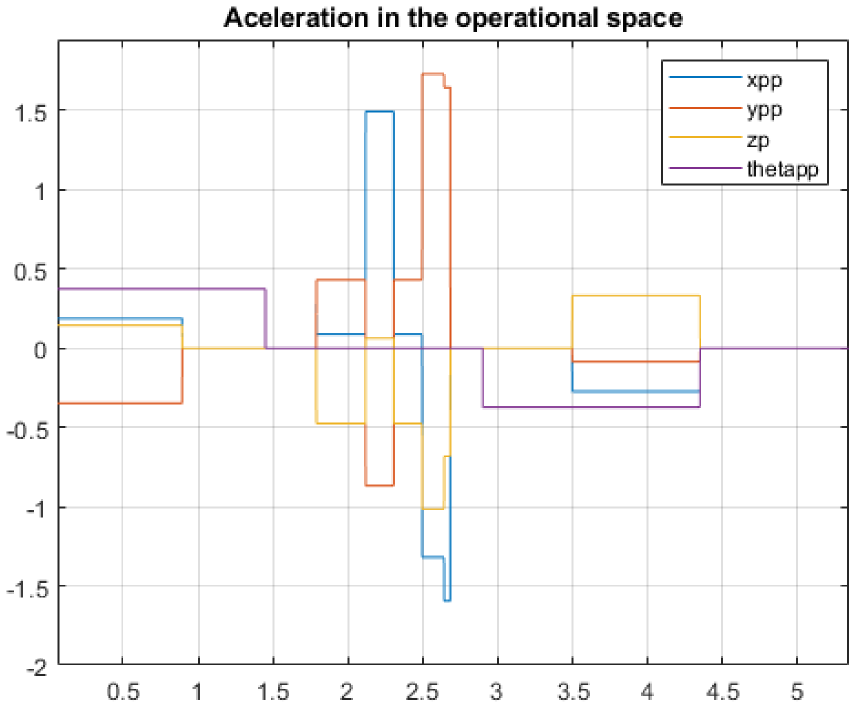


Figure 16: Accelerations in operational space

In figure(17) the joint trajectory obtained by inversion of the kinematics are shown. Each line represents one of the joint's variables, named with 'd' for the prismatic joint and with 't' for the revolute one:

- $q_1 = d_1$
- $q_2 = d_2$
- $q_3 = d_3$
- $q_4 = t_4$

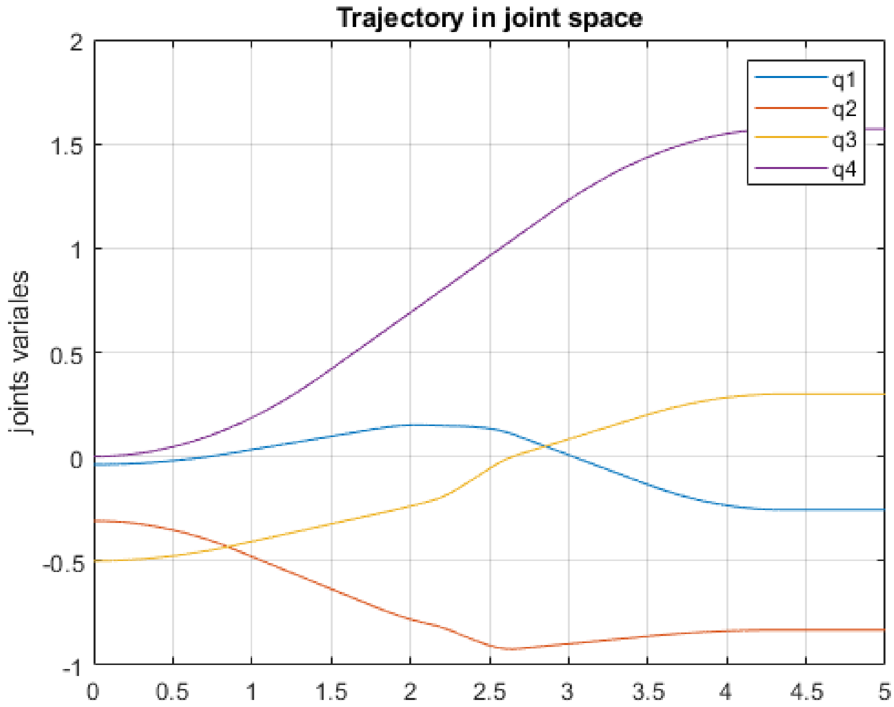


Figure 17: Trajectory in the joint space

The last step of this first part of the thesis project is related with the generation of a code able to produce an animation figure(18) of the considered robot configuration following the path described before.

Useful to create this simulation environment are the homogeneous transformation matrices that connect each joint to the base frame. After that, all these HT matrices are connected between them in order to create the arms of the robot using the 'mesh' function in MATLAB. Starting from a selected trajectory in the operational space the robot moves following the path with the end-effector. Using the inverse kinematics algorithm, the trajectories at the level of the joints are obtained

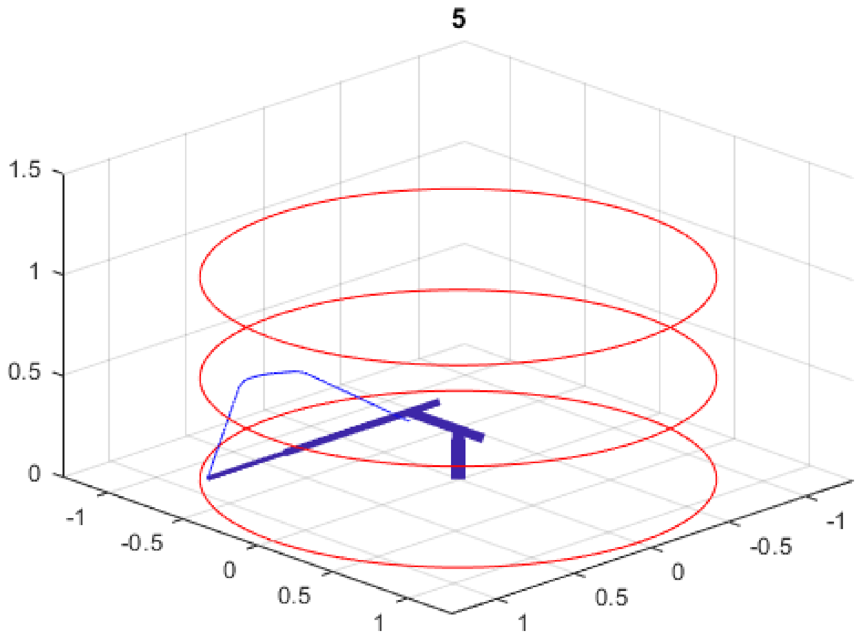


Figure 18: Trajectory in the operational space traveled by the robot

4 Interaction model

One of the crucial steps of the project is to build the model of the used machine and of the interaction between the end-effector and the material to be shaped. The starting model of the CNC machine, developed by the prediction team, is composed by electrical and mechanical equations that can synthesize the machine work and implementation.

In particular, the mechanical part is related with a cutter that has 2 degrees of freedom, an horizontal movement and a rotational one while the electrical part is due to the electric motors that actuate the machine. For what concerns the interaction model,it is developed around the friction coefficient present between the tool and the material; this is because it is the crucial parameter, playing the main role in the tool wear process.

4.1 CNC machine model

The first step to perform for the MOREPRO project is to build a simplified model of the system that could synthesize how the machine works. This model is used for different applications:

- in the Plant; here the equations are used to simulate the real system and by giving appropriate inputs it is possible to analyze the output of the machine and study how it changes with different values of the parameter,
- in the Extended Kalman Filter block, where the system model is used in order to estimate the state variables.
- in the Extended Kalman Filter for system identification; here the model is used in order to estimate the values of the unknown parameters of the system.

The starting model is composed by different equations that describe the electric and mechanical behaviour of the machine. In particular, the electrical equation concerns the DC motors that are used to move the axes of the machine while the mechanical ones are related with the cutter. For what concerns the tool, it is modeled as a cutter that performs a linear and angular movements.

$$\begin{cases} \ddot{\theta} = \frac{k_t i_a}{I_n} - \frac{Att_{mot}\dot{\theta}}{I_n} - \frac{\beta F_c \dot{\theta}}{I_n} \\ \ddot{x} = \frac{F_1}{m} - \frac{F_c(F_2\alpha + c)}{m} \\ \dot{i_a} = \frac{V_s}{L} - \frac{Ri_a}{L} - \frac{k_v\dot{\theta}}{L} \end{cases} \tag{11}$$

The state variables of the system are:

- $\dot{\theta}$: rotational velocity
- $\dot{x}$: linear velocity
- i_a: dc current of the motor

The inputs of the EKF, as well as those of the real model are:

- V_a: armature voltage
- F_1: horizontal force that moves the cutter
- F_c: function that defines the contact with the object. It is supposed to assume 2 values:
  $$\begin{cases} 1 : \text{when there is contact between the cutter and the object} \\ 0 : \text{when there is no contact} \end{cases}$$

The model parameters are:

- β: friction coefficient
- L: inductance of the motor
- m: the cutter's mass

The first model is as simple as possible, and then it is improved adding more information about the interaction between the workpiece and the cutter.
In order to estimate the tool's wear, a new formulation about the friction coefficient is added because this parameter is believed to have a major impact on the usury.

4.2 Friction coefficient models

Describing the metal cutting process is very difficult; the complexity is related to the plastic deformation that arise during the shaping of the workpiece. The thermomechanical deformations that occur in the metal bring to micro-structure modifications while the main causes involved in the tool wear, is the high temperature at the tool-workpiece interface. The increasing temperature in the metal cutting, is due to the sliding contact between the metallic surfaces; this kind of motion generates high friction coefficients that dissipate huge amount of energy which is even higher when tool wear occurs. The tool-chip interaction surface, figure(19) [5], can be divided into

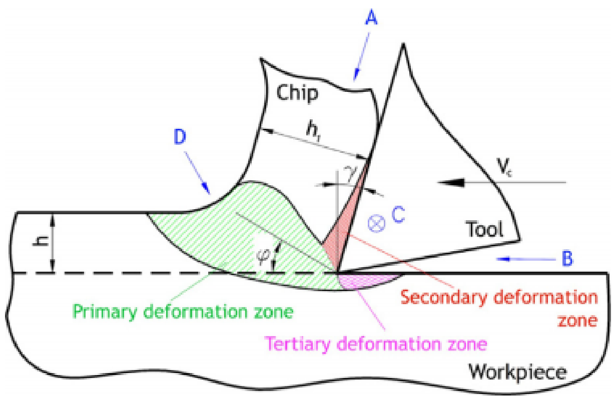


Figure 19: Deformation zone in tool-workpiece interface

three zones that differ from one another for mechanical characteristics related to the impact; understanding the temperature in the primary and secondary deformation zone is important for comprising the level of stress during the cutting procedure. Along the tool-chip interface [6] the regions are respectively called sticking region, transition region and sliding region. Two different kinds of deformation take place in this area:

- in the sticking region a plastic deformation is present;
- in both transition and sliding region there is an elastic deformation.

The friction coefficients in metal cutting process are influenced by many factors; among the most important there are temperature, the used material of the tool and of the workpiece, the relative speed in the interactions, the applied forces and the cooling media supplied in the contact interface. One way to decrease this friction is for sure the use of cutting fluids, like lubricant oils, whose effect is more evident at low speeds. At high speeds the cooling is not able to lubricate the interaction surface with the consequence that the effects are reduced and the friction coefficients are almost the same of the dry condition. In general the whole behaviour is also related to the amount of lubricant provided to the machine.

To accurately describe and model the metal cutting procedure, detailed mathematical models are needed which are able to represent how the material deform but also how the tool and the workpiece interact. The state of art related with the friction coefficient in metal machining provides a lot of models that consider different factors and parameters that could influence the interactions. The goal of this study is to better understand which, between the factors, has a greater influence on the friction coefficient.

Among the many approaches studied, several were discarded because of the excessive difficulty in finding the parameters, while less detailed models have been taken into consideration, which in any case give satisfactory results but are also easier to implement. In the following paragraphs some of the considered models are shown but only the last one is used to build the model implemented in MOREPRO. The final model was developed in teamwork choosing two different models that can be merged.

4.2.1 Friction modelling related with cutting force

The first considered model, takes into account the interaction between the cutter and the workpiece from a mechanical point of view; the aim of the following study is to find a relation between the friction coefficient and the forces acting during the cutting. The whole modelling procedure is heavily influenced by the chosen friction model. This model is developed in a mechanistic approach, this means that the cutting force is estimated applying a mathematical formulation to each small element obtained by dividing the cutting edge.

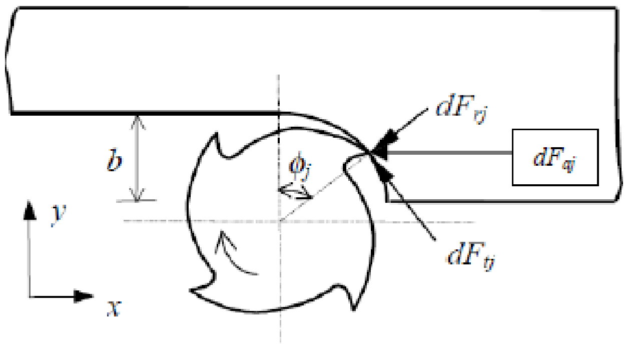


Figure 20: Milling process diagram

As shown in figure(20), considering the point of interaction between the tooth and the workpiece three forces are identified, dF_t, dF_r and dF_a in the tangential, axial and radial direction. As mentioned in [7] the three forces can be found by the following equations:

$$dF_t(\phi, z) = K_t h_j(\phi, z)dz$$

$$dF_r(\phi, z) = K_r dF_t(\phi, z) = K_t K_r h_j(\phi, z)dz$$

$$dF_a(\phi, z) = K_a dF_t(\phi, z) = K_a K_t h_j(\phi, z)dz$$

where h_j is the cutting point's thickness, K_r, K_t, K_a are the cutting force coefficients and ϕ is the shear angle, that is the angle between the point of incidence of the tooth and the vertical. In order to find the friction coefficients the three forces dF_t, dF_r and dF_a must be written in x,y and z direction as follows:

$$dF_x(\phi) = dF_t cos(\phi) + dF_r sin(\phi)$$
$$dF_y(\phi) = dF_t sin(\phi) - dF_r cos(\phi)$$
$$dF_z(\phi) = dF_a$$

The friction coefficient is computed in the following way:

$$\beta = tan\left[arctan\left(\frac{dF_y(\phi)}{dF_x(\phi)}\right) + \gamma\right]$$

This formulation of β is related to the immersion angle. Even though this model gives useful information from a mechanical point of view, it is nevertheless discarded because some parameters are laborious to find. It has been observed that increasing the difficulty of the used model does not necessarily mean improving the accuracy of the final model. Very often more complicated models involve slight variations in the friction coefficient.

The next treated model, on the other hand, deals with many geometric parameters that are easily known and also have greater impact on the coefficient of friction.

4.2.2 Influence of machining speeds in friction coefficient

Between the main parameters that affect the friction coefficient there are the machining speeds: cutting speed and feed rate, which have a combined effect in the cutting process. The influence of these parameters strongly depends on the lubrication conditions the machine is working on; the possible situations are: dry, minimum quantity lubrication (MQL) and wet machining. Usually the dry processes are not used because of the high friction coefficient that develop from the sliding contact between the tool and the workpiece, and this high friction values leads to an early tool wear and this means high costs for maintenance. Also a wet machining process has high costs due to the high amount of cutting fluids but also from an environmental point of view. A good compromise between this two conditions is the MQL, able to allow a reasonable tool life and limited costs.

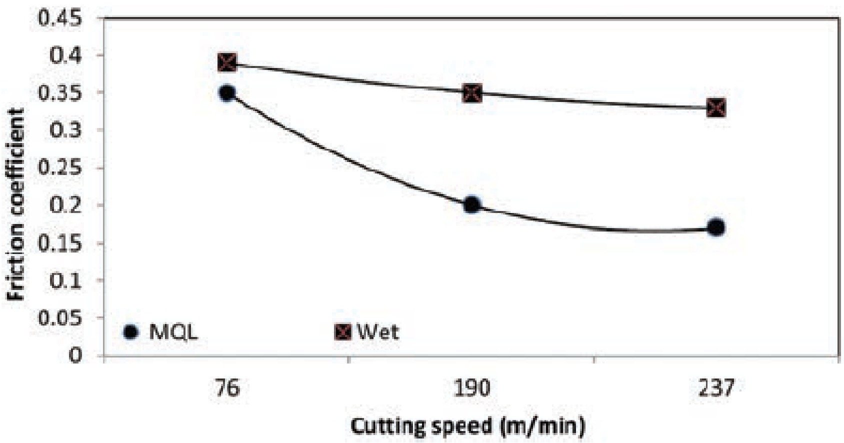


Figure 21: Variation of the friction coefficient related with cutting speed in different conditions.

As shown in the image above, figure(21), the friction coefficient is very influenced by the cutting speed, in particular in the MQL conditions. The goal of this model [8] is to build a friction coefficient formulation that takes into consideration the acting speed during the milling process:

$$\beta = 3.32 V_c^{-0.45} - 0.24 f \tag{12}$$

where V_c is the cutting speed and f is the feed rate.

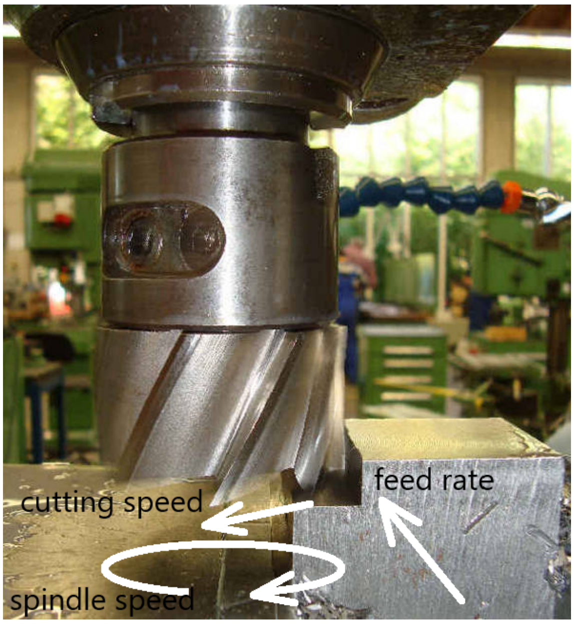


Figure 22: Machining speeds representation.

To go more into details, the two speeds can be defined as below [**?**]:

- the cutting speed, figure(22), is a relative velocity between the cutter of the CNC machine and the material to be processed and in particular it means how fast the workpiece moves through the the cutting tool. The unit of measurement is in surface feet per minute (sfm) or meters per minute (m/min) and is represented as a tangential linear velocity with respect to the cutter. Each material has an ideal cutting speed to be worked on and knowing all the other parameters the formula to calculate it is the following:

$$V_c = \frac{\pi DCn}{1000}. \tag{13}$$

  where DC is the diameter of the cutting tool and 'n' is the spindle speed (the rotational frequency of the spindle of the machine of which unit of measurement is in revolutions per minute (rpm).

- the feed rate is the relative velocity at which the cutting tool is advanced along the material piece to be shaped. The feed units depends on the metal cutting process, [mm/rev] in for rotating workpiece and [mm/min] for not rotating one. This rate is represented as a perpendicular vector with respect to the cutting speed.

$$fr = nTcl. \tag{14}$$

where 'n' is the spindle speed, t is the number of teeth of the cutter and cl is the chip load or feed per tooth.

4.3 Model identification for MOREPRO

This step of the work is performed in teamwork and foresees the union of two formulations related with the friction coefficient β; this union is made in order to create a model as close to reality as possible and that considers more influencing factor.

Below there is an explanation and a demonstration of the result obtained adding the examined model into the plant of the system and filling it with possible values taken from experimental data.

The first formulation taken into consideration for the final model is the one of the equation(12), related with the cutting speed and the feed rate of the CNC machine during the milling process.

The used values of V_e and of f are respectively between 70÷230 mpm and 0.08÷0.47 mmpr. Filling the equation(12) with the mentioned values the friction coefficient's range is between $0.15 < \beta < 0.45$ figure(23).

A further study of the model is done replacing the equations (13) and (14) into the

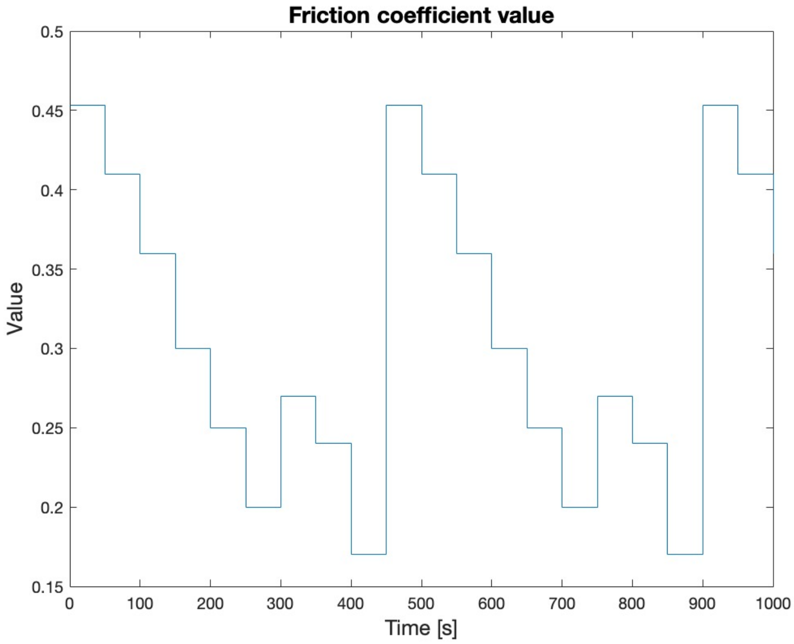


Figure 23: β as function of the feed rate and cutting speed

equation (12). The final formulation is the following:

$$\beta = 3.32 \left(\frac{DCn\pi}{1000} \right)^{-0.45} - 0.24(TnCL). \tag{15}$$

where 'n' is the angular velocity of the spindle.

In this way the new formulation(15) is a function of the input of the plant 'n', all the other parameters are constant or measurable, like the diameter and the temperature, while the chip load is the only variable parameter that impacts the wear conditions of the cutting tool.

The values of the chip load are assigned to the plant, and they change in a range of values 0.1÷1.1; this is the variable to estimate in the Extended Kalman Filter Bank in order to estimate the tool's state.

In figure(24), the friction coefficient is following the trend of 'n', the angular velocity of the cutting tool (spindle speed) and the range is $0.22 < \beta < 0.77$.

[$0.32 < \beta < 0.57$.]

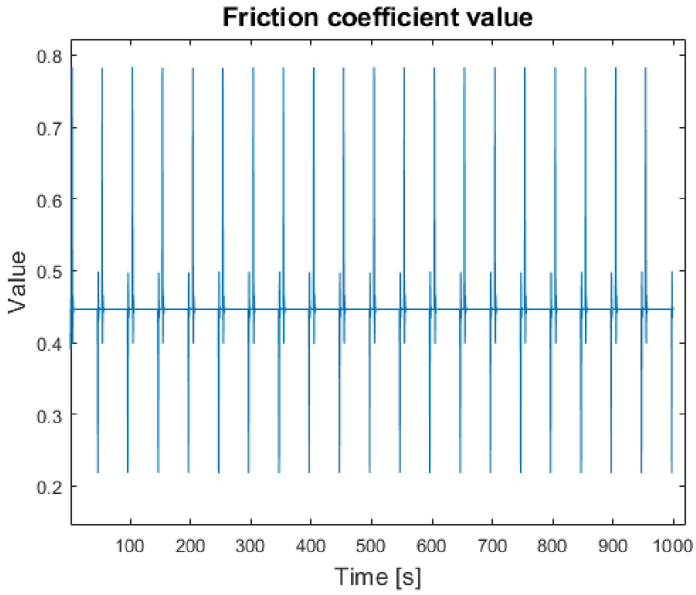


Figure 24: β function of the spindle speed

What is done in the following steps is to add to the previous model another one [9] which takes into account the aspect of temperature. In this case, the interaction between the tool and material is simulated with a temperature dependent friction model. The friction coefficient in this case is constant and equal to $\beta_0 = 1/\sqrt{3}$ while the temperature is less than T_0.

For temperatures higher than T_0, β decreases due to the thermal softening effect depending on the melting point temperature T_m and the power m_r, which is an empirical parameter.

$$\beta = \beta_0 \left[1 - \left(\frac{T - T_0}{T_m - T_0} \right)^{m_r} \right] \tag{16}$$

Using this equation(16) and the filling it with values of $550 < T < 480$, the trend of the coefficient is in the range $0.38 < \beta < 0.43$ figure(25).

The last step to perform for the final interaction model is to combine the previous

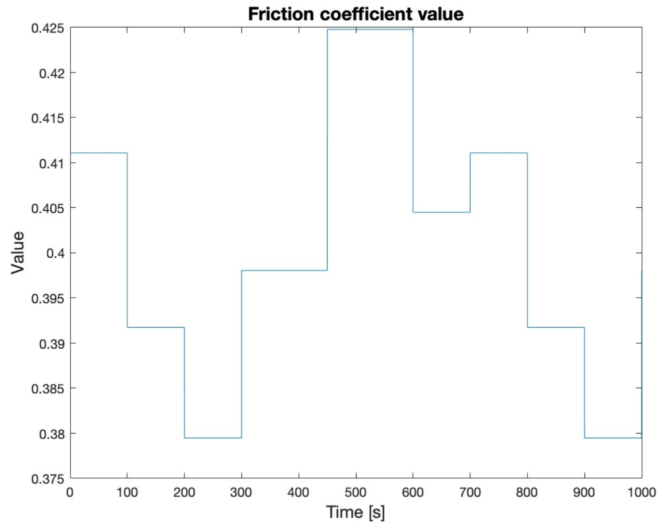


Figure 25: β obtained from the second model

formulation that have a great incidence on the values of the friction coefficient; for this reason the model related with temperature and the one related with the machining speeds are joined.

The global formulation is obtained by replacing the β formulation (15) instead of β_0 into (16) with the following result:

$$\beta = \left(3.32\left(\frac{DCn\pi}{1000}\right)^{-0.45} - 0.24(TnCL)\right) * \left[1 - \left(\frac{T - T_0}{T_m - T_0}\right)^{m_r}\right] \tag{17}$$

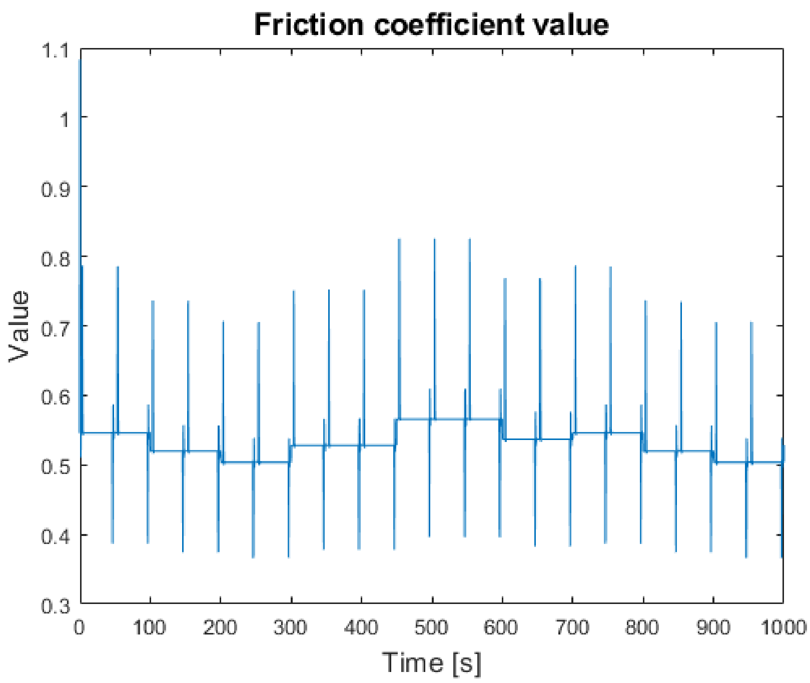


Figure 26: Global effect on β coefficient

We can notice that in the final equation the parameters involved are all geometric or that can be directly measured by sensors except of the chip load, which therefore becomes the parameter to be estimated because it is directly related to the tool wear. Chip Load affects five major areas of the machining process:

- Controls the required force to cut the work material
- Assists in controlling heat
- Controls tool wear
- Directly affects the metal removal rate
- Directly affects surface finish

The chip load setting is still an open topic since too much chip load leads to increased wear, brings a premature tool failure, rough finishes and draws more torque and amperage through the machine, also lets the stress on the axis drives to increase.

For too little chip load what happens is that the appearance of vibrations and chattering that will chip the tool's cutting edges and it can cause the tool to rub and wear rather than cut.

Substituting beta equation into the system's state equations gives:

$$\begin{cases} \ddot{\theta} = \frac{k_t i_a}{I_n} - \frac{Att_{mot}\dot{\theta}}{I_n} - \frac{(3.32(\frac{DC\dot{\theta}\pi}{1000})^{-0.45} - 0.24(t\dot{\theta}CL)) * [1 - (\frac{T - T_0}{T_m - T_0})^{m_r}]F_c\dot{\theta}}{I_n} \\ \ddot{x} = \frac{F_1}{m} - \frac{F_c(F_2\alpha + c)}{m} \\ \dot{i_a} = \frac{V_s}{L} - \frac{Ri_a}{L} - \frac{k_v\dot{\theta}}{L} \end{cases} \tag{18}$$

The nominal parameters of the machine are:

	Nominal value
Mass [kg]	3
Radius [m]	0.3
Resistance [kΩ]	0.6
Inductance [mH]	0.1
Torque constant	1.5
Voltage constant	0.2
Motor Inertia [kgm^2]	0.001
T_0 [°C]	400
T_m [°C]	1400
Diameter of cutter [mm]	100
Number of teeth	5

Table 2: Nominal CNC parameters updated

4.4 Model implementation in the predictive algorithm

For clarity and in order to give a greater collocation of the complete model obtained in equation(18), in the following paragraph an explanation of the predictive algorithm for wear estimation is given. The model of the CNC machine, as mentioned before, is started from a simple model and subsequently is updated adding more details, in particular the interaction between the end-effector and the workpiece. The implementation of the previous modeling takes place in almost all the blocks of the predictive algorithm, developed by the prediction team. The predictive algorithm is the core of MOREPRO project and is composed by four different blocks:

1. **Plant of the system**. The first block is composed by the CNC machine dynamic model and is meant to simulate the real system. The outputs of the system are important for the estimation of the tool's wear.

   It is easy to understand that it is cheaper and more advantageous to simulate the system in a virtual environment instead of performing real tests, which require more time and are more expensive.

2. **Extended Kalman Filter bank**. The second block sees the implementation of the EKF algorithm which uses a series of measurements observed over time in order to produce an estimates of unknown variables. Inside the predictive algorithm different filters are implemented, each differs from the others for the different values of the friction coefficients, based essentially on different values of chip load. The inputs for this block are the same of the plant; the outputs of this system are the computation of the angular acceleration and current calculated on the base of the different chip load. A comparison is done between the angular acceleration and current estimated and the real ones obtained from the plant, with the production of an error.

3. **Logic of decision and management**. The third block deals with the choice of the best model relying on the minimum integral error.

4. **System identification**.My personal contribution is given by the implementation of this block.

   In order to estimate the unknown parameters of the system and Extended Kalman Filter is also implemented for the system identification problem. The inputs are the same of the EKF's bank while the outputs are the estimated parameters. The last block is explained in the following chapter.

5 System identification

The last step of this thesis work is related with the system identification.
System identification means estimate the possible values of the unknown parameters that are inside the model, in order to build the final dynamical model. This procedure is followed when the system is undetermined, which means that the number of parameters is higher than the number of the equations. There are many possible ways to follow but the basic idea that is implemented to solve this problem is to use the inputs and outputs measured from the system in order to build the mathematical relations between the parameters.
The system identification can be done in two possible way [10]:

- gray box: the model of the system is available but there are different unknown parameters to be estimated.
- black box: the model is not available, the whole estimate of the parameters is done only building connections between the inputs and outputs values.

The parameters estimation for this thesis work is done using an Extended Kalman Filter for parameters identifications.

5.1 Extended Kalman Filter for parameter estimation

The Extended Kalman filter is a method to estimate both the states of the system and also its parameters; it is an iterative procedure, composed by different equations that are fast evaluated as the system changes during time.
In each step there is the estimation not only of the system parameters but also of the covariance matrices, uncertainty indicators of the parameters estimation.
In order to perform the system identification there is a need of a state space model describing the parameters of the system [11].

Starting from the following state-space model in a discrete-time domain:

$$
\begin{aligned}
x_{k+1} &= f\left(x_k, u_k\right) + w_k \\
y_k &= g\left(x_k, u_k\right) + v_k
\end{aligned}
\tag{19}
$$

where x_k are the states, u_k are the inputs, y_k is the output, w_k and v_k are the disturbances.

It's possible to write the state space model for parameters estimations:

$$
\begin{aligned}
\theta_{k+1} &= \theta_k + r_k \\
d_k &= g\left(x_k, u_k, \theta_k\right) + e_k
\end{aligned}
\tag{20}
$$

Denoting with θ_k the parameter, r_k is the noise introduced in the parameters, in order to simulate their variation over time and e_k is the noise introduced by the sensors in the output equation.

The output equation of the EKF for system identification is the same of the output equation of the state space model. Given these two equations and the inputs and outputs of the system, the system identification can be performed.

As reported in [12] and [13],the steps to follow are:

Definition Determine

C_k^θ which is a matrix built with the first-order Taylor-series used to linearize the output equation with respect to the parameters.

$$
C_k^\theta = \left.\frac{\mathrm{d}g\left(x_k, u_k, \theta\right)}{\mathrm{d}\theta}\right|_{\theta=\hat{\theta}_k^-}
$$

Initialization

In the first step the parameters and the error covariance are initialized with the best information. Even if this information is not accurate it is not a problem because the EKF method has a fast convergence to the answer.

For k=0, set

$$\hat{\theta}_0^+ = \mathbb{E}\left[\theta_0\right]$$
$$\Sigma_{\tilde{\theta},0}^+ = \mathbb{E}\left[\left(\theta_0 - \hat{\theta}_0^+\right)\left(\theta_0 - \hat{\theta}_0^+\right)^{\mathrm{T}}\right]$$

Computation

For each iteration, two estimates of the parameters (θ) and of the covariance matrix (Σ) are performed; $\hat{\theta}_k^-$ and $\Sigma_{\tilde{\theta},k}^-$ are the first estimates and are computed before any measurement of the system is performed, for this reason this is called prediction step.

After taking the output measurements, the previous estimates are updated to $\Sigma_{\tilde{\theta},k}^+$ and $\hat{\theta}_k^+$; this one is called correction step.

For $k = 1, 2, \ldots$ compute

State estimate time update: $\hat{\theta}_k^- = \hat{\theta}_{k-1}^+$

Error covariance time update: $\Sigma_{\tilde{\theta},k}^- = \Sigma_{\tilde{\theta},k-1}^+ + \Sigma_r$

Kalman gain matrix: $L_k^\theta = \Sigma_{\tilde{\theta},k}^- \left(C_k^\theta\right)^{\mathrm{T}} \left[C_k^\theta \Sigma_{\tilde{\theta},k}^- \left(C_k^\theta\right)^{\mathrm{T}} + \Sigma_e\right]^{-1}$

This matrix is an indicator of the uncertainty of the parameters estimate, higher is the uncertainty, higher is also the Kalman gain. Usually with the addition of the new information, the unpredictability decreases.

State estimate measurement update: $\hat{\theta}_k^+ = \hat{\theta}_k^- + L_k\left[y_k - g\left(x_k, u_k, \hat{\theta}_k^-\right)\right]$

Innovation vector: $\left[y_k - g\left(x_k, u_k, \hat{\theta}_k^-\right)\right]$

The updated parameter $\hat{\theta}_k^+$, is equal to the prediceted one $\hat{\theta}_k^-$, plus an innovation vector multiplied by the Kalman gain matrix (L). The innovation vector is the difference between the real output of the system (in our case the plant's simulation) y_k minus the output of the system computed with the estimated parameters $\hat{y_k}$.

Error covariance measurement update: $\Sigma_{\tilde{\theta}_k}^+ = \left(I - L_k^\theta C_k^\theta\right)\Sigma_{\tilde{\theta},k}^-$

5.1.1 Application of the EKF for MOREPRO model

In the following paragraph, it is described in a detailed way the application of the Extended Kalman filter for parameter identification for our system, the CNC machine. Considering the CNC machine model:

$$\begin{cases} \ddot{\theta} = \frac{k_t i_a}{I_n} - \frac{Att_{mot}\dot{\theta}}{I_n} - \frac{\beta F_c \dot{\theta}}{I_n} \\ \ddot{x} = \frac{F_1}{m} - \frac{F_c(F_2\alpha + c)}{m} \\ \dot{i_a} = \frac{V_s}{L} - \frac{Ri_a}{L} - \frac{k_v\dot{\theta}}{L} \end{cases} \tag{21}$$

the parameters to estimate are the following:

$$\theta = [K_t; In; m; F_2; L; Res; K_v]$$

with

- K_t: motor's constant
- In: inertia
- m: tool's mass
- F_2: contact force
- L: inductance of the motor
- Res: resistance of the motor
- Kv: motor's constant

The first step to perform in order to implement the Kalman filter for system identification is to find the Jacobian of the state-space model C_k^θ; it means to find the matrix whose elements are the partial derivatives of the function with respect to the parameters.

$$\hat{C} = \begin{bmatrix} \frac{i_a}{In} & \frac{0.3\dot{\theta}}{In^2} - \frac{K_t i_a}{In^2} + \frac{\beta F_c \dot{\theta}}{In^2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{F_c c + F_2 \alpha}{m^2} - \frac{F_1}{m^2} & \frac{-\alpha F_c}{m} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{R i_a}{L^2} - \frac{V_s}{L^2} + \frac{K_v \dot{\theta}}{L^2} & \frac{-i_a}{L} & \frac{-\dot{\theta}}{L} \end{bmatrix} \quad (22)$$

After initializing both the parameters $\hat{\theta_0^+}$ and the error covariance Σ_θ^+ and having selected values for the Σ_r and Σ_e, the recursive process can start.

The whole system identification is implemented in Simulink environment as shown in figure(27), implemented as a MATLAB function; in the left side there are the inputs for the function coming from the plant of the system, while in the right side there are the outputs coming from the application of the EKF that are the estimated parameters.

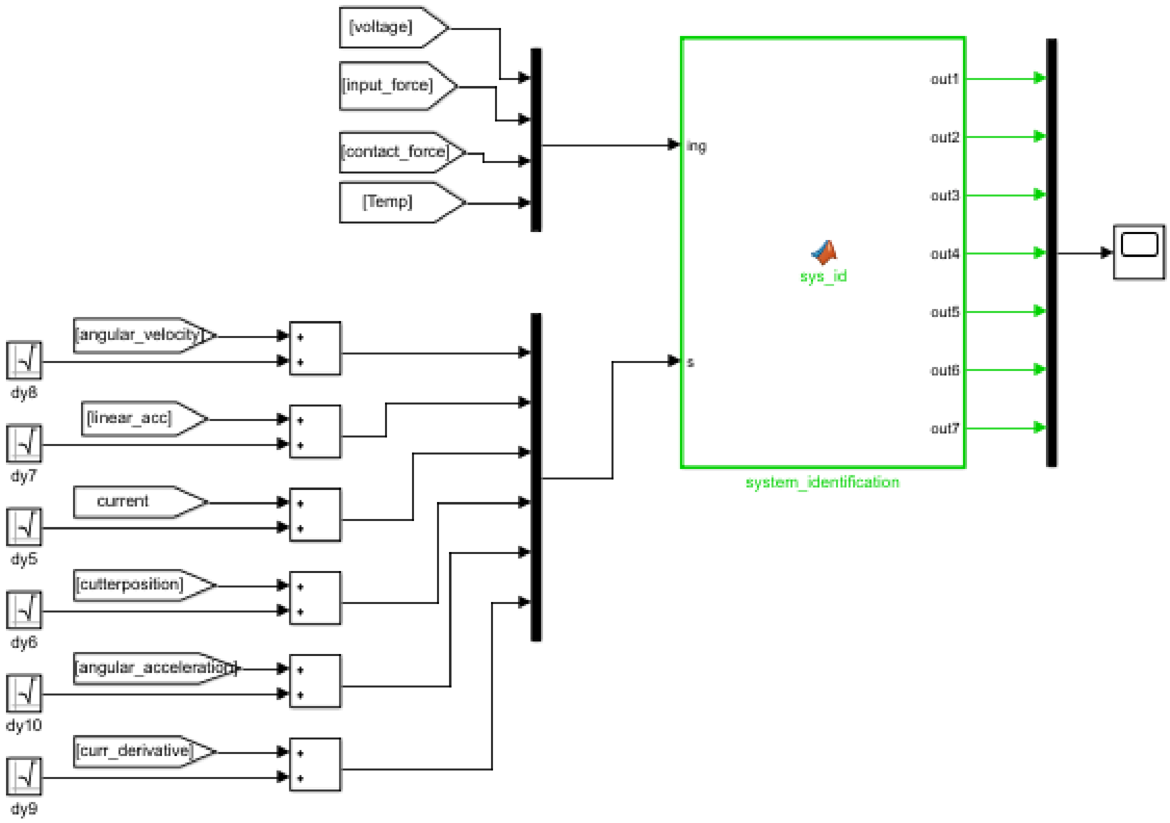


Figure 27: System identification using the EKF approach

5.1.2 Results

Following the steps explained in the previous paragraph the results obtained for the parameters estimation are shown below. Many of the estimated parameters with the Kalman Filter method are inside an acceptable range of values and reach stable values in a limited time frame. Analyzing more in detail:

- K_t after an initial swing, stabilizes at a values of 1.45
- K_v is stable around 0.358
- F_2 is the contact force between the tool and the workpiece; for this reason it is not a fixed values but it changes with time. The estimated range is between 0N and 5N.

- L has a value of 0.49H
- Res is stable at 0.28Ω

Unlike parameters that are correctly estimated, m and In have an increasing trend and for this reason it is not possible to identify a precise range. It is possible to say that it is not possible to find an estimate of this parameters with Kalman method because they are not correlated to the obtained data from the simulation.

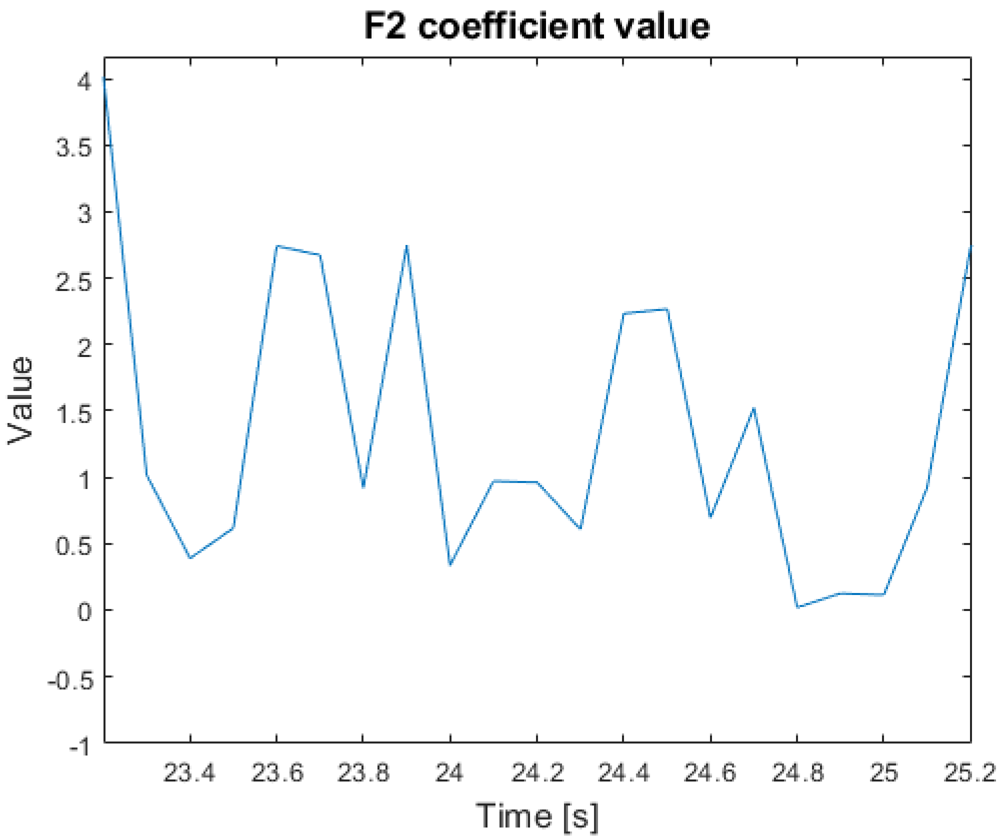
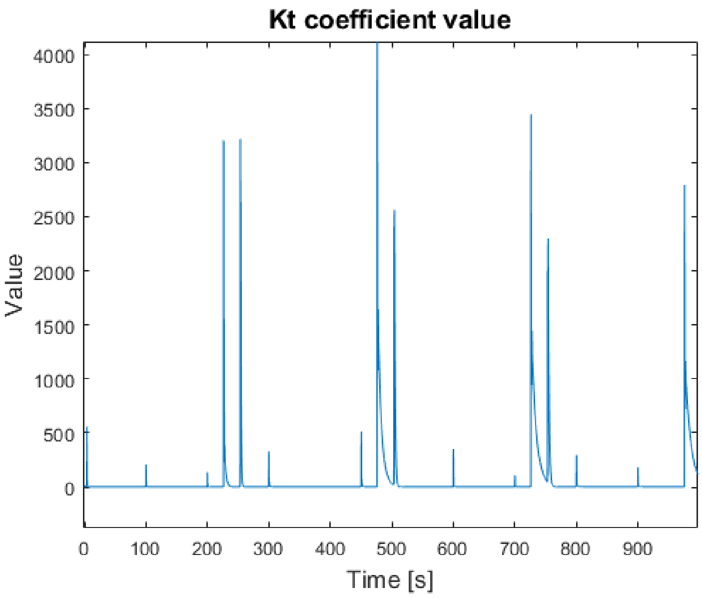
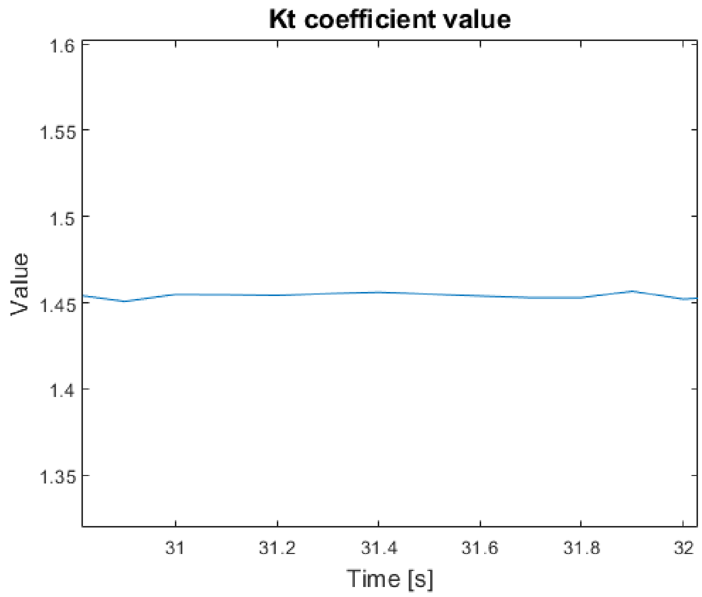


Figure 28: Trend of F2

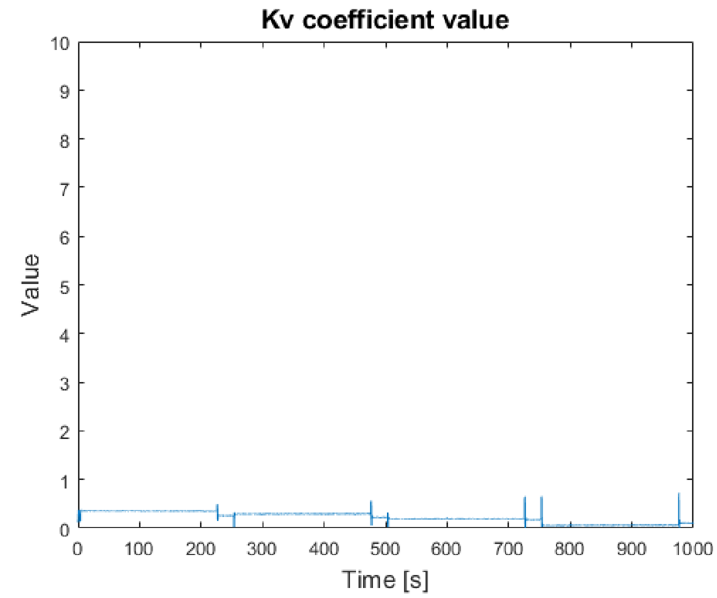


(a) Kt

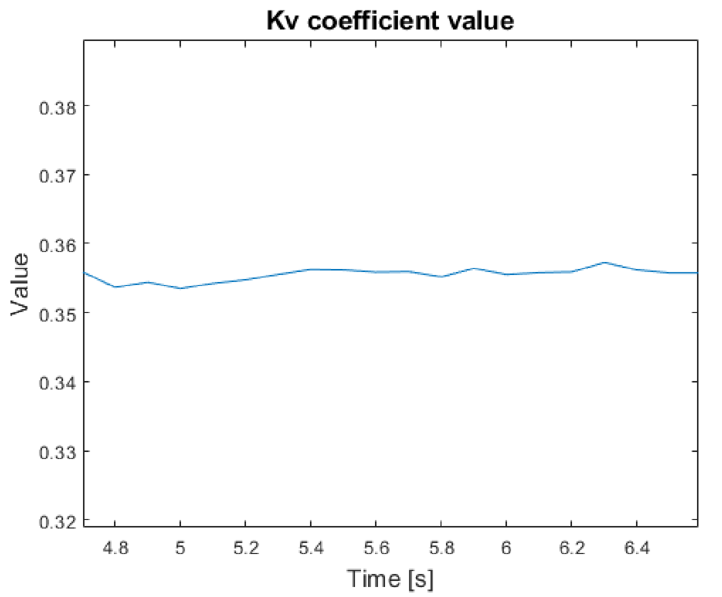


(b) Kt zoom

Figure 29: Trend of Kt

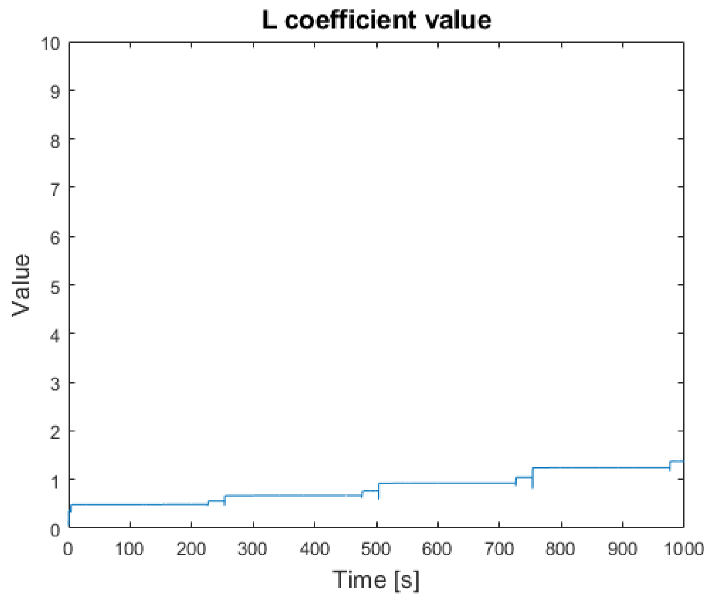


(a) Kv

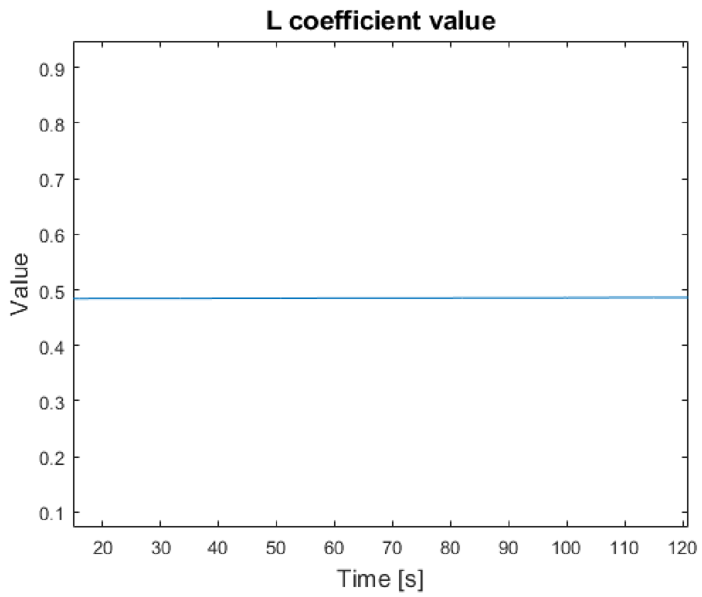


(b) Kv zoom

Figure 30: Trend of Kv

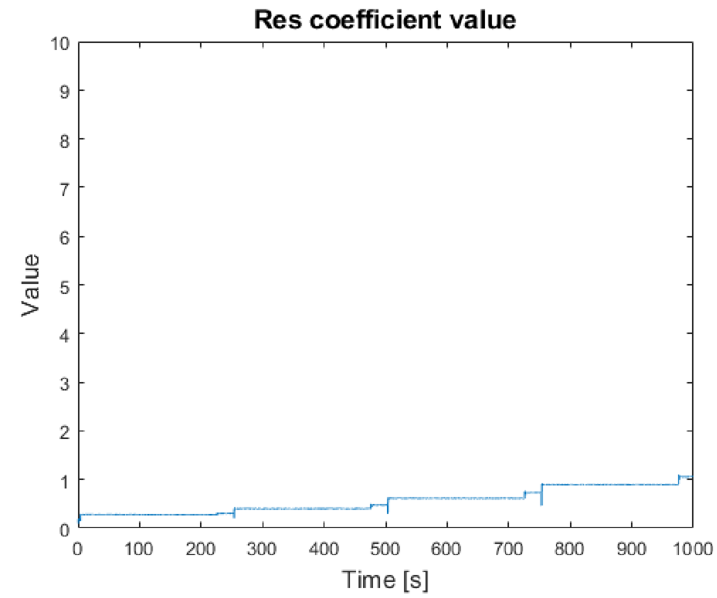


(a) L

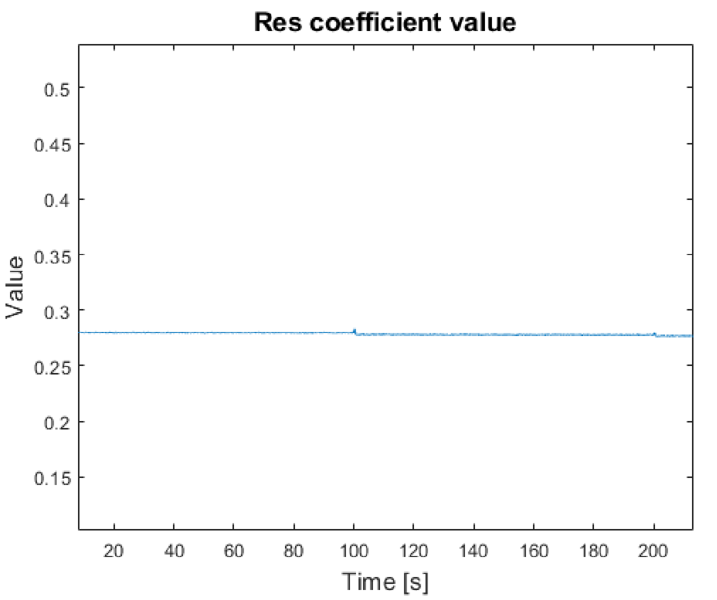


(b) L zoom

Figure 31: Trend of L

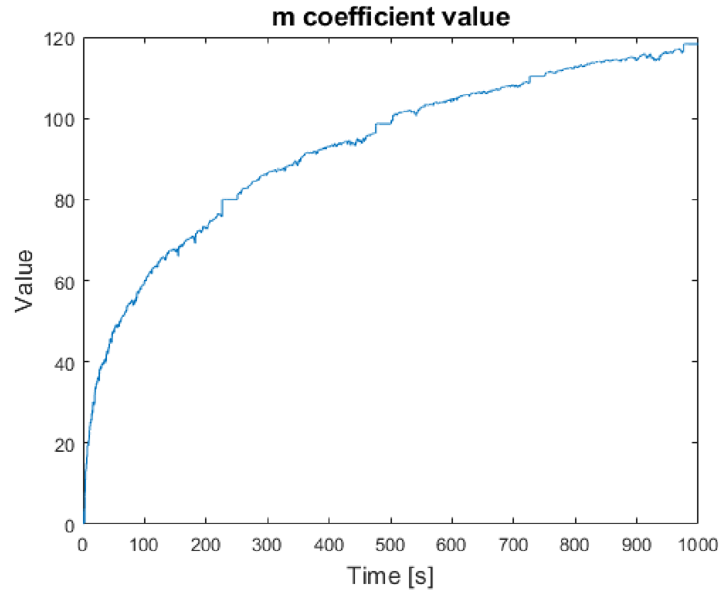


(a) Res

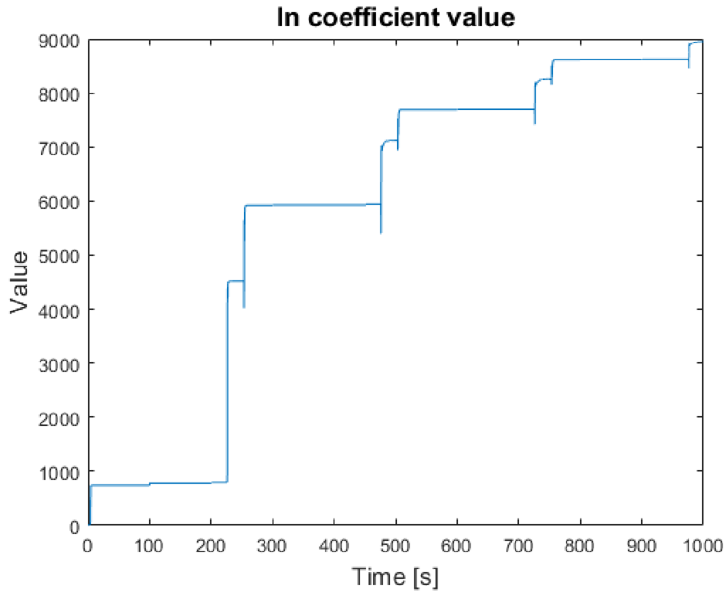


(b) Res zoom

Figure 32: Trend of Res



(a) Trend of m



(b) Trend of In

Figure 33: Parameters that are not within the expected range

6 Conclusions

At the end of this thesis work, with a very strong teamwork, the basics for MORE-PRO project are built. The prediction algorithm to estimate the state of health and the tool's wear is based on the evaluation of one parameter of the model called 'chip load', that as said before is the theoretical length of material that is fed into each cutting edge as it moves through the workpiece.

My contribution to this project is related with the following points:

- starting from the kinematics of the CNC machine, built an environment of simulation that in the future can be used and improved in order to replicate in 3D space the milling process;
- model of the interaction cutter-workpiece, implemented in the predictive algorithm.
  It would be useful for future work, to find others parameters affecting the interaction in order to increase the level of accuracy of the model and obtain an estimate of the tool's wear as close as possible to the real one;
- For last the system identification brings to good estimate of the parameters. Other techniques of model identification can be implemented with the purpose of finding the values also for the parameters that with the EKF are still not identified for lack of correlation with the used approach.

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ltering for battery management systems of LiPB-based HEV battery packs Part 2. Modeling and identification" (2004)