Blaž Florjanič, Karl Kuzman
University of Ljubljana, Faculty of Mechanical Engineering

Estimation of Time for Manufacturing of Injection Moulds Using Artificial Neural Networks-based Model

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Summary

One of the most crucial activities for a successful business is project time and cost estimation. This is an early estimation process which is usually handled by highly skilled, in-house experts. One of the main obstacles in this process is to accurately define the relationship between product properties and the machining hours necessary to manufacture the mould. This article suggests how to address this problem by using artificial neural networks (ANN). The developed model shows that it is possible to achieve admissible accuracy of the estimation by using easily obtainable input data.

KEY WORDS:
artificial neural networks
mould making
injection moulding
estimation process
manufacturing hours

KLJUČNE RIJEČI:
alatničarstvo
injekcijsko prešanje
umjetne neuronske mreže
procjenjivanje
sati izrade

Procjena vremena potrebnoga za izradu kalupa za injekcijsko prešanje s pomoću modela temeljenoga na umjetnim neuronskim mrežama

Sažetak

Jedna od najvažnijih aktivnosti u izvedbi projektno orijentiranih poslovnih procesa ocjena je potrebnih tehnoloških vremena i troškova. To je rana faza procjene koju provode visoko kvalificirani interni stručnjaci. Jedna od najvećih zapreka u toj fazi je precizno definiranje odnosa između karakteristika proizvoda i potrebnih tehnoloških vremena za izradu kalupa. Ovaj rad predlaže pristup rješavanju tog problema korištenjem umjetnih neuronskih mreža. Razvijeni model pokazuje da je moguće postići prihvatljivu točnost procjene korištenjem lako dostupnih ulaznih podataka.

Introduction

The mould making industry is project driven, and as such it has to cope with the characteristics of individual production process. One of major sources of risk in project management is an inaccurate forecast of project costs, demand, and other impacts.[1] In the mould manufacturing process it is crucial to minimize risks in the project estimation phase. This is an early project stage in which different resources are estimated. One of the important estimations is also the necessary number of manufacturing hours. The estimation phase is commonly a human expert driven activity which is sensitive to the expert's bias. This bias can lead to an underestimation of project resources, when the estimator is overconfident, or to over-estimation of project resources when the estimator does not have sufficient confidence that all aspects of the project can be properly covered. Both scenarios, based on the expert's estimation, have a negative impact on the future business decisions. In case of underestimation, the project will bring economic loss, and in case of overestimation, it will most likely be assigned to a competitive supplier. The estimator's key competence is to properly collect and evaluate all the information which is significant for making the project estimation. The paradigm lies in the fact that the estimator should spend minimal time necessary on estimation activity, since in the mould-making industry usually less than 10% of all offers turn into orders, as stated in [2,3,4].

The estimation process

The research objective is to develop an estimation model which helps an expert to improve the estimation of manufacturing hours in the mould manufacturing. Figure 1 shows that unsupported expert estimation represents a very broad solution space. This is mainly due to limited information availability, the expert's limited capability of simultaneously processing multiple information, and the expert's bias. By using artificial neural networks (ANN) supported expert estimation the solution space gets narrower as shown in Figure 1. It is very important to properly position the supporting estimation model in the expert process. By using a supported estimation process the risk of underestimating or overestimating the manufacturing hours is minimized.

In this article manufacturing hours represents the total of all machining hours spent to complete all parts of the mould. In each operation machining time, the loading time and unloading time are taken into account. This means that only the hours when machines are actually occupied are taken into account.

ANN output retrieved from the developed model is categorized as an evaluation indicator for the expert to confirm the results or re-evaluate and correct them accordingly. This is an empirical model that learns from past examples and generalizes the solution for new cases. When implementing ANN the most vital step is to define an appropriate set of parameters that capture the properties of part geometry and represent them as a mould complexity, which most significantly influences the volume of manufacturing hours.

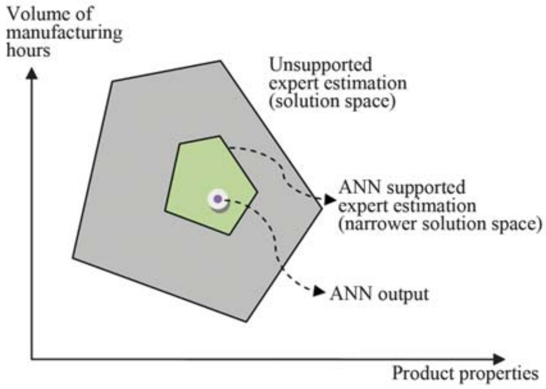

FIGURE 1 – Expert estimation solution space

A major challenge of the estimation process in general is to achieve sufficient accuracy within minimal time consumption for this operation. Estimation accuracy is directly related to the data that we have at our disposal at the moment in which the estimation process takes place. As shown in Figure 2, the availability of data differs during the different project phases. As we move along the timeline of the project the availability of data increases, as well as its accuracy. Consequently, estimation uncertainty and risk decreases, so more accurate results can be expected. Estimation methods differ in accordance with the project stage in which they are used:[3,6,7]

– intuitive,
– analogical,
– parametric, and
– analytical.

Intuitive estimation methods are based on the human expert's prior knowledge and experience. A major downside to these methods is that the results are very susceptible to many different subjective factors. So, the results obtained face problems regarding accuracy and repeatability. These problems can be reduced to a certain extent by applying methods that use more than one estimator.[8] A major benefit of these methods is moderate time consumption. They are usually applied in early project stages.

Analogical estimation methods are based on finding successful projects with similar characteristics like the estimated one. On the basis of detected similarities corresponding values are assigned to the estimated project. These methods become applicable when the basic product shape is defined. They are also considered as conditionally reliable methods since the relations between similarities are usually estimated by an expert.[8] Their main strengths are transparency of gained results and the ability to achieve the solution rapidly. These methods strongly rely on the database of previous projects, and become unreliable if proper mapping of similar characteristics cannot be obtained.

Parametric estimation methods are used to make estimations on the basis of parameters that are able to directly translate the properties of the product or project into an estimated value. These methods are built on the databases of past projects. Estimations are obtained by collecting input parameters and processing those to formulate a proper estimation impact. These methods are usually seen as *black box* solutions. A major challenge is in defining a proper set of input parameters. These methods offer both speed and sufficient accuracy if used properly. By keeping the database of a past project open and adding the data of new projects, this model gains the ability of adaptation and learning, which comes forward significantly when used properly with ANN platforms. Parametric methods are prone to use both parametric and non-parametric models which were found to give acceptable estimates.

Analytical estimation methods are applicable when both product data and manufacturing technology are defined in detail. They are usually applicable in the latter stages of the product life cycle. The estimation is made on a detailed breakdown of the complete process into elementary tasks.[5] For every task relations between inputs and corresponding outputs are analytically determined. These methods are usually rigid and relations between parameters are not easily modified. They do not have adaptation ability.[5] The gained results give the most accurate estimations. Their major downsides are time consumption and limited applicability in the early project stages.

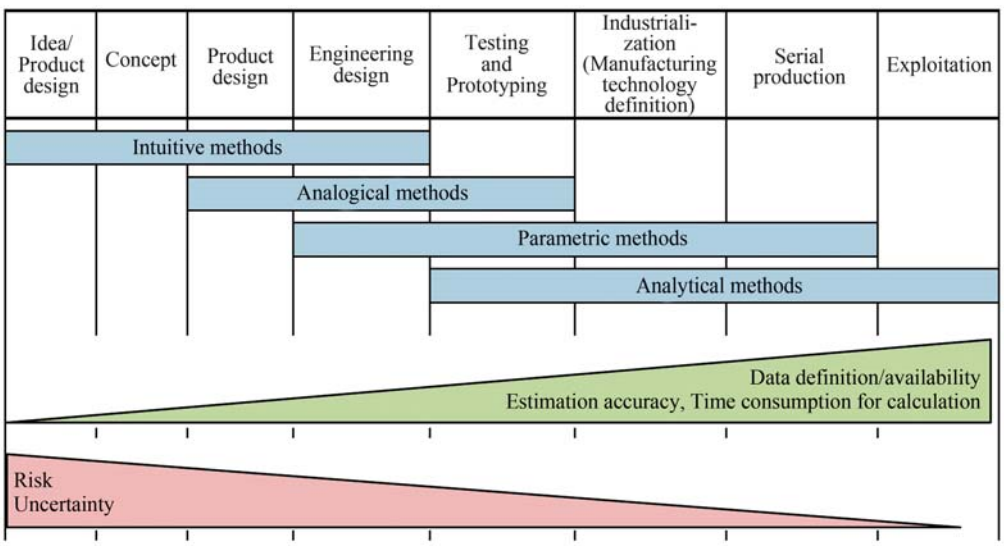

FIGURE 2 – Estimation methods applicable in different stages of the project (product life-cycle)

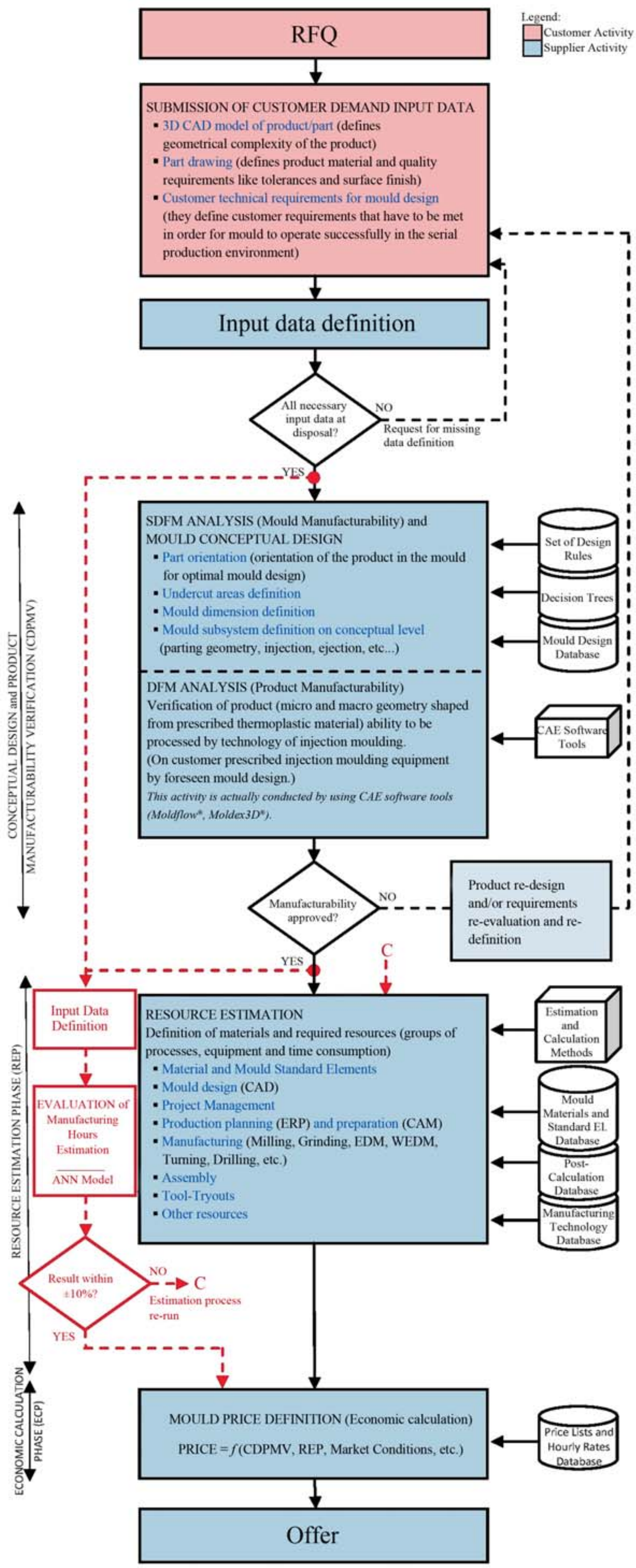

FIGURE 3 – Systematic expert driven estimation process supported by ANN

In the mould making business the most commonly used practice are human intuitive methods,[6] or a combination of intuitive and analogical methods. Mould makers put a major emphasis on retrieving accurate project estimation with minimal time consumption, because a large number of quotations have to be processed in order to achieve sufficient order load. The reason for that lies in a very moderate success rate of all submitted offers. In order to achieve a sufficient level of result credibility, the estimation process has to be systematically approached. The complete estimation process consists of several phases, and in each phase different solving solutions are available. A detailed step-by-step model of the expert driven estimation approach was developed for this research and it is shown in Figure 3. The diagram gives precise instructions how the expert should approach the estimation. This model fits into intuitive methods. The left side of the diagram shows in which part of the process the ANN response (estimation), which is part of this research, is used. By implementing ANN the unsupported estimation process is upgraded to supported estimation process (see Figure 1).

An overview of previous work

Review of significant recently published literature and articles is presented in structured form in Table 1. They are sorted in regards to the used estimation method. The table also defines for which industry the research was done and what problem they were trying to solve. The majority of research activities in this field are focused on defining estimation models that are able to define the link between geometric characteristics of the product and price/cost of the product/project. By focusing on these economic values, the estimating process is contaminated by influences that do not possess technical characteristics of the manufacturing process. These are actually influences of the market, reflecting request and demand, and have very little to do with technological issue. To achieve a successful business process on the shop floor production process planning is crucial. To deal with this issue it is necessary to use estimation models which predict the volume of manufacturing hours. Articles which are the most significant for this research are related to product complexity,[9,10,11] and the implementation of ANN in the mould estimating process.[9,12] All these approaches give quite accurate estimates when used for very specific types of products

Artificial neural network model

The solution can be approached by different models (regression, genetic programming, ANN, etc.). Using ANN is an efficient way to solve complex problems. ANN are recognized as universal approximators. They represent a valid alternative, especially when relationships are not known and cannot be logically argued[13]. When using the ANN approach the system is decomposed into simple

TABLE 1 – Literature overview

Method	Source	Method sub-type (ANN , Regression, Case-Based Reasoning, …)	Industry (Mould-making, Construction, …)	Problem solving
Analogical	[2] Fonseca et al.	Retrieval of similar data from database	Mould Making / Tools for injection moulding	Assisting mould quotation
	[3] Duverlie et al.	Case Based Reasoning	Product Design	Cost estimation
	[15] Wang et al.	Case Based Reasoning	Mould Making	Mould cost estimation
Parametric	[9] Raviwongse et al.	ANN	Mould Making	Mould complexity computation
	[6] Ficko et al.	Case Based Reasoning	Mould Making/ Tools for Sheet Metal Forming	Manufacturing costs estimation for stamping tools
	[7] Farineau et al.	Regression model	Product Design	Cost estimation
	[13] Cavalier et al.	Regression model, ANN	Automotive	Production cost estimation
	[12] Che	ANN	Mould Making and Injection moulding	Product and mould cost estimation
	[16] Farineau et al.	Regression model	Product Design	Cost estimation
	[17] Elhag et al.	Regression model, ANN	Construction/Buildings	Tender price estimation
	[18] Verlinden et al.	Regression model, ANN		Sheet metal parts cost estimation
	[19] Kim et al.	Regression model, ANN, Case based Reasoning	Construction/Buildings	Construction costs
Analytical	[4] Denkena et al.	Rule-based	Mould Making/ Tools for die casting	Die cost calculation
	[10] Fagade et al.		Mould Making and Injection moulding	Lead time estimation
	[11] Fagade et al.		Mould Making and Injection moulding	Lead time estimation
	[20] Chan et al.		Mould Making / Tools for injection moulding/ Toy industry	Mould cost estimation
	[21] Denkena et al.	Accessibility Analysis	Mould Making/ Tools for injection moulding and die casting	Manufacturing cost calculation
	[22] Chin et al.	Decision Tables	Mould Making	Mould cost estimation
	[23] Fagade et al.	Boothroyd-Dewurst Dixon-Poli	Mould Making	Product and mould cost estimation
	[24] Fagade et al.		Mould Making and Injection moulding	Product and mould cost estimation
	[25] Nagahanumaiah et al.		Tools for injection moulding and die casting	Die or mould cost estimation
	[26] Navodnik et al.		Mould Making	Mould cost estimation
	[27] Menges et al.		Mould Making	Mould cost estimation
	[28].Kazmer		Mould Making	Mould cost estimation

elements – in this case neurons, which can be seen as computational units which are fed with inputs that initiate a certain response. Connections between neurons determine information flow, which determines network behaviour.

For solving the estimation task a multi-layer feed-forward network is used. For ANN training a *Levenberg-Marquard* algorithm is used. It is a method which is fast and most appropriate for training moderate-sized, feed-forward neural networks[14]. The training process objective is to tune weights in order for the network to behave as expected when it is presented with certain inputs.

The performance function for feed-forward networks is a mean square error (MSE), which defines the average squared error between the network outputs (y_i) and the target outputs (t_i).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \qquad (1)$$

The methodology for the creation of estimation model consists of three major phases which are input definition, ANN definition, and model validation, as shown in Figure 4. After the model is approved by an expert it is ready for implementation. If the selected variables do not properly describe the relationship between inputs and expected outputs, optimization takes place and the model is re-evaluated.

Architecture of ANN

The ANN architecture foreseen for this model is shown in Figure 5. It consists of 27 inputs in the input layer, less than 10 neurons with a sigmoid activation function in the hidden layer, and one neuron with a linear activation function in the output layer. Software used for ANN modelling is MATLAB.

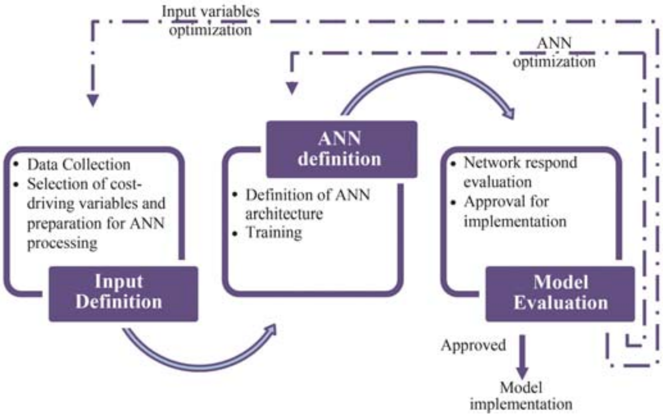

FIGURE 4 – Estimation model creation

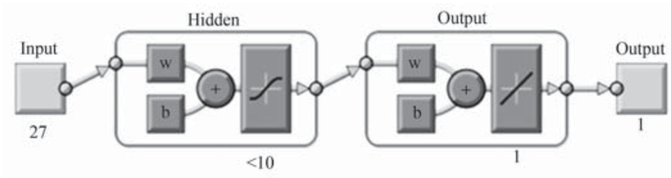

FIGURE 5 – ANN architecture

Process variables

These variables should properly describe the factors that significantly influence the manufacturing hours. The most influential sets of factors in this case are (see Figure 6):

- micro and macro part geometry and quality requirements, prescribed b a 3D CAD model, part drawing, and special technical requirements;
- technical requirements for the injection mould, which define environment in which the mould will operate in serial production (moulding facility);
- mould design principles/rules;
- production environment in which mould manufacturing takes place (mould shop equipment, organization, technology utilization, corporate culture, etc.).

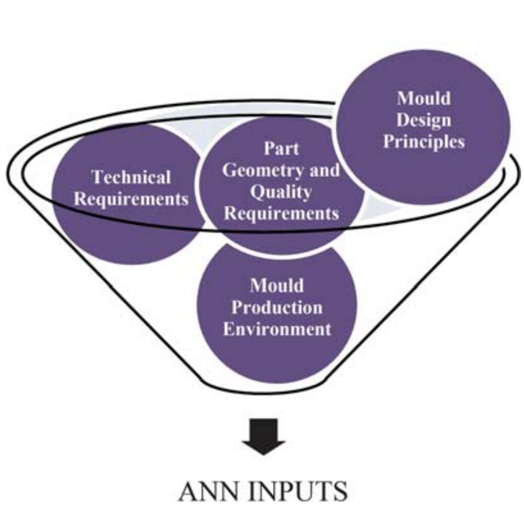

FIGURE 6 – Dominant factors defining ANN inputs

Process variables used in this ANN model describe the first three sets of significant factors, while the production environment influence is captured within the expected network response.

In the ANN model design phase expert opinion was taken into account when initial parameters, described in the following text, were foreseen:

- *part envelope length* (L_P) (Part envelope width, length, and height define the bounding box around a properly oriented product. All three dimensions are aligned with orthogonal mould axis. The width and length lie on the *xy* plane, while the height lies on the z axis direction (Figure 7). The latter is also the direction of mould opening and closing. This parameter is represented by a positive real number in ANN. The same applies for W_p and H_p.);
- *part envelope width* (W_P);
- *part envelope height* (H_P);
- *part surface area* (S_P) (Part surface area defines the total surface area of the product. This parameter is represented by a positive real number in ANN.);
- *part volume* (V_P) (Part volume defines the total volume of the product. This parameter is represented by a positive real number in ANN.);
- *nominal part thickness* (T_P) (Nominal part thickness defines the base thickness of the product. This parameter is represented by a positive real number in ANN.);
- *part material* (M_P) (In general, thermoplastic materials are divided in two major groups according to their molecular structure: amorphous and semi-crystalline. Both groups further divide thermoplastic materials according to their performance into high performance, engineering, and commodity (Figure 8). This parameter influences the mould design rules. In ANN this parameter is represented by a vector with six entries.);
- *surface area of part projection* (S_{PA}) (The surface area of part projection is observed in the direction of mould opening dimension (*z* axis). This dimension influences the size of the machine, which is necessary for processing the observed product. This parameter is represented by a positive real number in ANN (Figure 7).);
- *envelope volume* (V_E) (Envelope volume represents the volume of bounding box around the product. This parameter is represented by a positive real number in ANN.);
- *part complexity/cavity detail* (CX_p) (Part complexity is divided into three categories: simple/low detail, moderately complex, or complex. In ANN this parameter is represented by a vector with three entries.);
- *overall dimensional tolerance requirements of the part* (DT_P) (Dimensional requirements of the product are commonly defined on the drawings. These requirements define manufacturing precision of mould parts and consequently influence the duration of mould manufacturing. Overall dimensional tolerance requirements are categorized in six categories: class 1 (<0.01), Class 2 (<0.05), Class 3 (<0.1), Class 4 (<0.5), Class 5 (<1), and Class 6 (<1). In ANN this parameter is represented by a vector with six entries.);
- *number of cavities* (N_C) (In this case we are investigating 1+1 cavity moulds, which mean that this parameter holds Value 2 across the database. This parameter is represented by a positive real integer number in ANN.);
- *mould length* (L_M) (This parameter is defined by mould design rules. It is represented by a positive real integer number in ANN. The same applies for W_M and H_M.);

– *mould width* (W_M);
– *mould height* (H_M);
– *parting line/surface complexity* (CX_{PL}) (Parting surface complexity is divided into three categories: simple/flat, moderately complex (smoothly shaped, small steps), or free-form (complex, non-tangential surfaces, big steps). In ANN this parameter is represented by a vector with three entries.);
– *number of sliders per cavity, injection side* ($N_{S,IS}$) (Parts of product geometry that cannot be ejected in the direction of the main mould opening are called undercut areas. In order to assure the ejection of the product, these areas must be released prior to or during the ejection with special mechanical elements like sliders, lifter cores, unscrewing mechanisms, etc. External undercuts are usually released by sliders and internal undercuts by lifter cores (Figure 9). This parameter is represented by a positive real integer number in ANN. The same applies for $N_{S,ES}$, $N_{LC,IS,}$ and $N_{LC,ES}$.);
– *number of sliders per cavity, ejection side* ($N_{S,ES}$);
– *number of lifter cores per cavity, injection side* ($N_{LC,IS}$);
– *number of lifter cores per cavity, ejection side* ($N_{LC,ES}$);
– *ejection (EJ)* (Ejection principles can be structured in several different ways. For the purposes of this article a simplified categorization into basic two categories was formulated: simple/single stroke and multiple strokes. They are sufficient to cover all the results in the database of this research. In ANN this parameter is represented by a vector with two entries.);
– *injection system (IS)* (For the purposes of this article injection systems are categorized into three basic categories: cold runner systems, hot runner systems, and combined systems. In ANN this parameter is represented by a vector with three entries.);
– *cavity material, injection side* ($M_{C,IS}$) (Cavity materials are commonly divided into two categories: non-hardened or pre-hardened (1.1730, 1.2311, 1.2312, etc.) and hardened steel (1.2343, 1.2344, 1.2083, 1.2767, etc.). Applying the material from a different category influences the production technology and consequently the consumption of manufacturing hours. In ANN this parameter is represented by a vector with two entries. Same applies for $M_{C,ES}$.);
– *cavity material, ejection side* ($M_{C,ES}$);
– *surface finish, injection side* (SF_{IS}) (Product surface finish significantly impacts the number of manufacturing hours. It is crucial to assure proper final machining operations in order to achieve the required surface finish. Eight basic categories mould surface finishes are used: rough machined, fine milled/machined, fine EDM, polished with sandpaper (up to 800-grit), polished with sandpaper (up to 1,200-grit), high polished, high polished/class A surfaces, photo etched/texturized. In ANN this parameter is represented by a vector with eight entries. The same applies for SF_{ES}.);
– *surface finish, ejection side* (SF_{ES});
– *tool lifetime* (TL_{SPE}) (The standard mould classification defined by The Society of Plastic Engineers uses the following classes of moulds: Class 101 (one million or more cycles), Class 102 (not exceeding one million), Class 103 (under 500,000 cycles), Class 104 (under 100,000 cycles), and Class 105 (not exceeding 500 cycles). All samples in this research are categorized as high production moulds and belong to Class 101.)

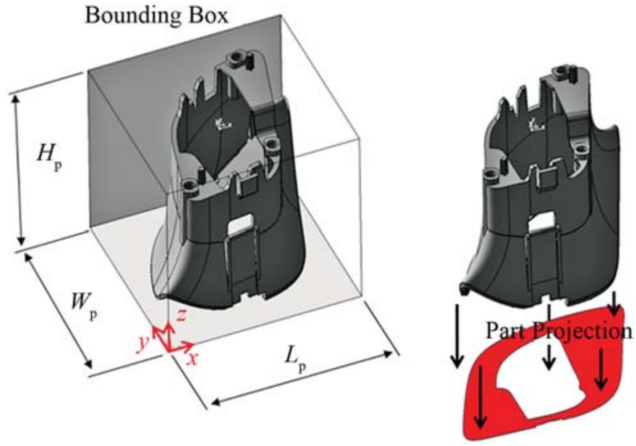

FIGURE 7 – Bounding box, part envelope width, length and height, and surface area of part projection

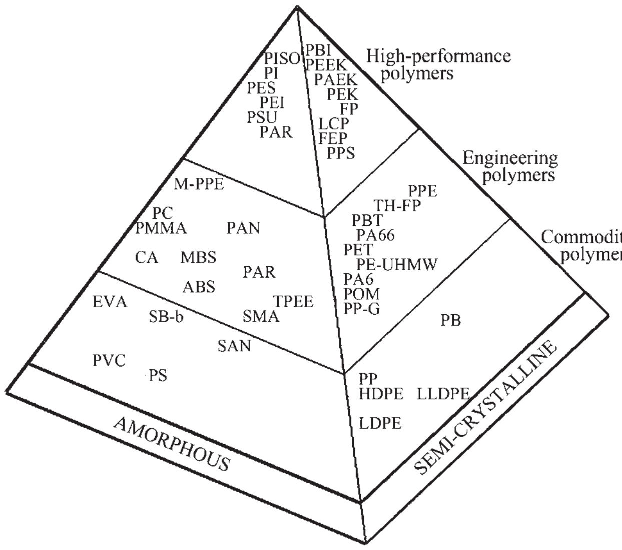

FIGURE 8 – Polymer performance pyramide[26]

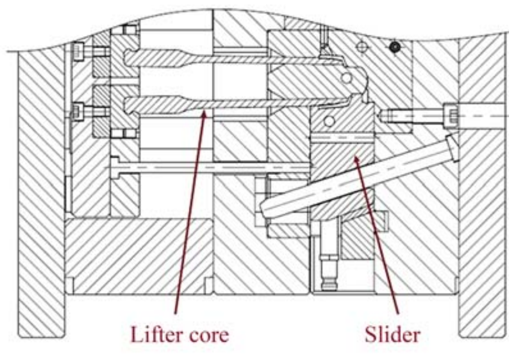

FIGURE 9 – Sliders and lifter cores

Validation of the model

Obtaining a large number of cases in an individual production represents a certain obstacle, because companies hold this information as internal know-how.

For the purposes of this research 105 cases were investigated. These samples were obtained from a mid-sized mould shop. They are typical automotive industry projects when the injection mould holds the mirrored part geometry. These are usually referred to as 1+1 cavity moulds (see Figure 10). By narrowing the research to a certain type of moulds, improved results are expected and a narrower and denser decision space is achieved.

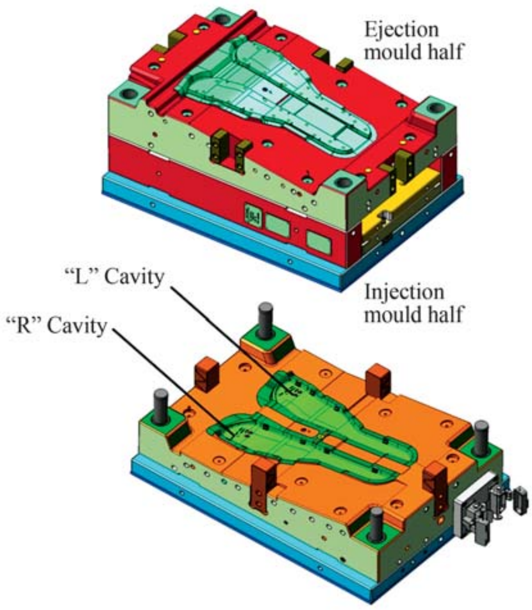

FIGURE 10 – Example of typical injection mould for automotive industry holding geometry for mirrored parts

In order to overcome the obstacle of restricted number of samples a multifold cross-validation procedure is performed. Input data is divided in five subsets, each containing 21 samples (Figure 11). The network is trained five times. Each time one of the subsets is left out. Four (4) subsets are used for training while the fifth subset is used for measuring the accuracy of the network response.

Subset 1 Validation set	Subset 2 Training set	Subset 3 Training set	Subset 4 Training set	Subset 5 Training set
Subset 1 Training set	Subset 2 Validation set	Subset 3 Training set	Subset 4 Training set	Subset 5 Training set
Subset 1 Training set	Subset 2 Training set	Subset 3 Validation set	Subset 4 Training set	Subset 5 Training set
Subset 1 Training set	Subset 2 Training set	Subset 3 Training set	Subset 4 Validation set	Subset 5 Training set
Subset 1 Training set	Subset 2 Training set	Subset 3 Training set	Subset 4 Training set	Subset 5 Validation set

FIGURE 11 – Multifold cross-validation on 5 subsets

Evaluation of the network response for each validation set is carried out through the observation of validation error, measured as error (E), relative percentage error (RPE), root mean square error ($RMSE$), and mean absolute percentage error ($MAPE$).

$$E = y_i - t_i \tag{2}$$

$$RPE = \frac{y_i - t_i}{t_i} \cdot 100 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2} \tag{4}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - y_i}{t_i}\right| \tag{5}$$

Before collected data was submitted to the ANN model, further input optimization was performed with data encoding as follows.

The majority of samples from the database only belong to one of two groups of thermoplastic materials (M_p): semi-crystalline engineering polymers or amorphous engineering polymers. Only six samples belong to one of the other four groups. Due to this observation, the initial vector with six entries was reduced to two entries, one representing amorphous thermoplastic polymers, and the other representing semi-crystalline thermoplastic polymers. For further input simplification encoding [-1, 1] is used to describe parameter value as a single entry.

The collection of data for *surface area of part projection* (S_{PA}) was found as time consuming (more than 15 minutes per sample), and therefore it did not meet an easy-to-obtain criterion. As result, it was removed from the model.

For part complexity/cavity detail (CX_p) encoding [-1, 0, +1] is used to transform a vector with three entries into a single entry. The same encoding is also used for parameters *parting line/surface complexity* (CX_{PL}), *injection system* (IS).

According to *overall dimensional tolerance requirements of the part* (DT_p) all samples are classified either in Class 3 or Class 4. Due to this observation, the initial vector with six entries was reduced to two entries. Encoding [0, 1] is used to describe the parameter value as a single entry. The same encoding is also used for parameters that are represented with all other vectors that have only two entries: *ejection* (*EJ*), *cavity material, injection side* ($M_{C,IS}$), *cavity material, ejection side* ($M_{C,ES}$).

Since all THE observed samples are 1+1 moulds, the parameter *number of cavities* (N_C) is constant across the database. This means that it does not contribute to the network response and that it can be left out from the model. The same applies for the parameter *tool lifetime* (TL_{SPE}) where all the samples *belong to Class 101.*

For parameters *Number of sliders per cavity, injection side* ($N_{S,IS}$) and *number of lifter cores per cavity, injection side* ($N_{LC,IS}$) the value is zero across the database. This means that they do not contribute to the network response and that they can be left out from the model.

When observing the parameters *surface finish, injection side* (SF_{IS}) and *surface finish, ejection side* (SF_{ES}) the majority of the sample belongs to one of four groups. The initial vector with six entries was reduced to three entries. Encoding [0, ½, 1] is used to describe parameter value as a single entry.

Complete set of 22 inputs with encoding is presented in Table 2.

Through an iteration process the number of neurons and layers was optimized having in mind the fundamental ANN rules of minimizing the output error and keeping network small. The ANN architecture used consists of 22 inputs in the input layer, four neurons with sigmoid activation function in the hidden layer and one neuron with linear activation function in the output layer.

As previously presented, multifold cross-validation was used to validate network response (see Figure 11). Input data were randomized and divided in five subsets, each containing 21

TABLE 2 – Inputs, output, and encoding

Inputs		Encoding	Inputs		Encoding
Part envelope length [mm]	L_P	True Value	Mould height [mm]	H_M	True Value
Part envelope width [mm]	W_P	True Value	Parting line/surface complexity	CX_{PL}	-1=Simple / Flat 0=Moderately complex (Smoothly shaped, Small steps) +1=Free-form (Complex, non-tangential surfaces, big steps)
Part envelope height [mm]	H_P	True Value	Number of sliders per cavity, Ejection side	$N_{S,ES}$	True Value
Part surface area [mm²]	S_P	True Value	Number of lifter cores per cavity, Ejection side	$N_{LC,ES}$	True Value
Part volume [mm³]	V_P	True Value	Ejection	EJ	0=Simple/ Single stroke 1=Multiple strokes
Nominal part thickness [mm]	T_P	True Value	Injection system	IS	-1=Cold runner system 0=Combined system +1=Hot runner system
Part material	M_P	-1= Semi-crystalline +1=Amorphous	Cavity material, Injection side	$M_{C,IS}$	0=Non Hardened or Pre-Hardened 1=Hardened steel
Envelope volume [mm³]	V_E	True Value	Cavity material, Ejection side	$M_{C,ES}$	0=Non Hardened or Pre- Hardened 1=Hardened steel
Part complexity /Cavity detail	CX_P	-1=Simple/ Low detail 0=Moderately complex +1=Complex/ High detail	Surface finish, Injection side	SF_{IS}	0=Polished with sandpaper, Fine EDM, Fine milled/ Machined ... 1/2=High polished 1=High polished-Class A surfaces
Overall dimensional tolerance requirements of the part	DT_P	0=Class 4 (<0.5), Class 5 (<1), Class 6 (>1) 1=Class 3 (<0.1), Class 2 (<0.05), Class 1 (<0.01)	Surface finish, Ejection side	SF_{ES}	0=Polished with sandpaper, Fine EDM, Fine milled/ Machined ... 1/2=High polished 1=High polished-Class A surfaces
Mould length [mm]	L_M	True Value	Outputs		
Mould width [mm]	W_M	True Value	Manufacturing hours	*VMH*	True Value

samples. The network was trained in five steps. At each step assigned subsets are left out. Four (4) subsets are used for training while the assigned subset is used for measuring the accuracy of the network response. At each step ANN was re-trained and validated five times. The average results were calculated per each sample.

For each subset error (*E*), relative percentage error (*RPE*), root mean square error (*RMSE*) and mean absolute percentage error *(MAPE*) are shown in Table 3. The overall network response returns *MAPE* 0.133, which is an acceptable result if used in an appropriate confidence interval. Average *RPE* for each sample is shown in Figure 12. It shows that the majority of results (96.2%) for the predicted manufacturing hours have *RPE* -25% or less.

$$AE = |y_i - t_i| \tag{6}$$

$$ARPE = \left|\frac{y_i - t_i}{t_i}\right| \cdot 100 \tag{7}$$

The comparison between network responds and target outputs shows an acceptable correlation coefficient 0.9254, as shown in Figure 13.

Negative and positive *RPE* represent underestimation and overestimation of estimation. Overestimation represents either profit or in the worst case a non-competitive offer, underestimation represents an unfavourable outcome, which represents itself in non-profitability of the project. *RPE* shown in Figure 12 was reshaped in histogram form as shown in Figure 14. By using the distribution diagram of *RPE* an expert gets good insight how results are distributed when using the proposed ANN model. The goal of an expert is, to operate in overestimation interval. This can be achieved by using safety multiplier. By

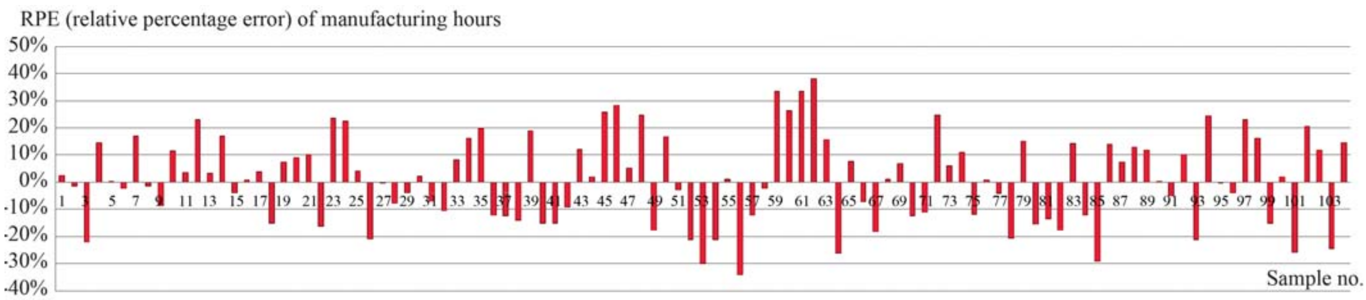

FIGURE 12 – Average RPE for each sample

TABLE 3 – Network response indicators

		Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Network
Output range	min	384	289	229	453	303	229
	max	1407	1209	1283	1604	2006	2006
RMSE Root mean square error		100.2	103.9	146.7	113.1	160.1	127.1
MAPE Mean absolute percentage error		0.085	0.124	0.192	0.123	0.140	0.133
E Error	max	252.1	209.0	296.3	186.8	334.0	334.0
	min	-208.1	-170.1	-204.8	-250.0	-204.9	-250.0
AE Absolute error	max	252.1	209.0	296.3	250.0	334.0	334.0
	min	1.8	3.7	11.7	5.4	1.4	1.4
RPE Relative percentage error	max	21.9%	20.9%	34.1%	26.2%	29.2%	34.1%
	min	-22.9%	-23.5%	-38.1%	-24.6%	-24.4%	-38.1%
ARPE Absolute relative percentage error	max	22.9%	23.5%	38.1%	26.2%	29.2%	38.1%
	min	0.3%	0.3%	1.0%	0.8%	0.3%	0.3%

multiplying ANN response with multiplier 1.15, eighty percent of all results are pushed into the overestimation interval. In case that more conservative approach is necessary, multiplier 1.25 can be used. In that case over 95% of all results are pushed into the overestimation interval.

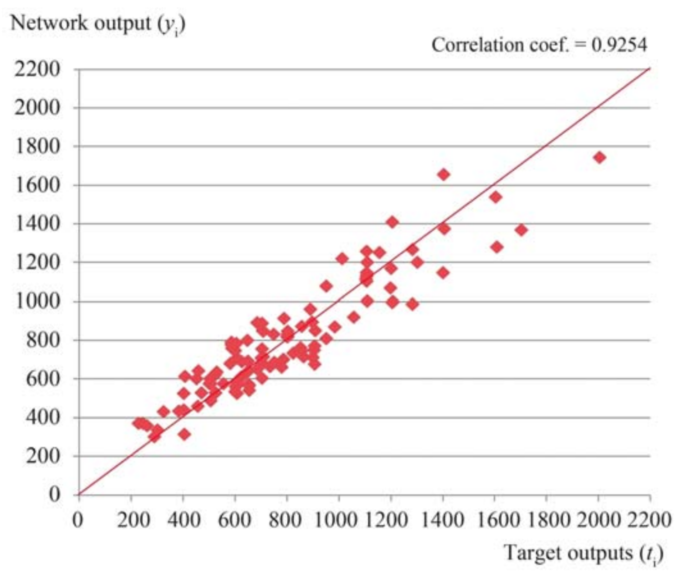

FIGURE 13 – Network outputs vs. target outputs

Discussion of using ANN model

The major benefit of using ANN model lies in the ability of defining relationships between parameters, when they are not known in either parametric or analytical form. Using ANN model for estimating manufacturing hours gives an expert a support for improving estimation accuracy, it shortens the time necessary for shaping decision in estimation process and assures repeatability of estimation results. The major concern when using this model represent cases when significant underestimation occurs.

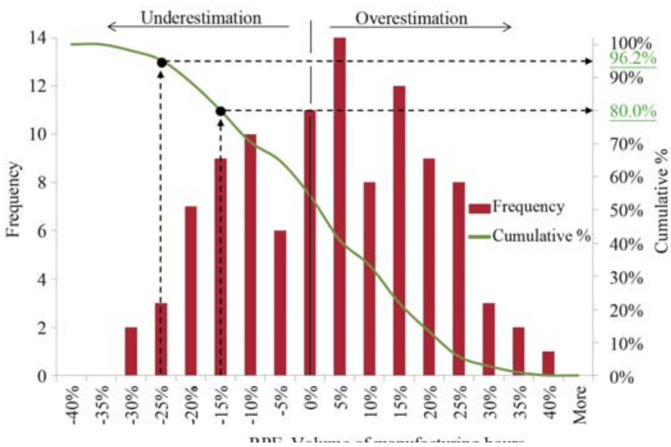

FIGURE 14 - Distribution of RPE

Conclusion

This article focuses on estimation of manufacturing hours, which is one of most important information in project estimation process. Developed estimation process (see Figure 3) supported by ANN model offers a bridge between expert-driven intuitive methods and data-driven ANN models. As difference to other authors this article focuses on manufacturing hours rather than cost-related economic values which contaminate the estimating process with non-technical influences.

The implementation of an approach shown in Figure 14 gives an expert instruction on how to process network response in order to achieve acceptable estimation confidence. This approach is conservative. The major role in this estimation process has a very specific production environment (individual production process) with consequentially limited number of cases on one hand, and on the other hand the assumption cannot be neglected that by implementing a limited number of parameters, the information is incomplete from a wider perspective. In decision making processes experts frequently rely on information that is incomplete. To overcome this obstacle, future research activities will consider implementation and development of a specially tailored expert elicitation model.

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CONTACT

Blaž Florjanič
University of Ljubljana
Faculty of Mechanical Engineering
Aškerčeva 6, SI-1000 Ljubljana
E-mail: blaz.florjanic@imold.si