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Application of machine translation techniques for the automatic selection of the technological process

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Abstract. This research deals with the problem of developing a design and technological documentation for a new product in terms of technological processes selection, according to the list of components from the product specification. Practical experience in the implementation of automated control systems in manufacturing enterprises of the machine-building industry and the latest technologies in the field of machine learning were used. The concept of using machine learning for automating the selection of technological processes was developed based on a list of components. As a technique of machine learning, the methodology sequence to sequence is proposed.

1. Introduction

Today, it is difficult to imagine an enterprise that does not use information technologies (IT). The interesting area is IT for the automation of processes in the manufacturing enterprise. Specialized software products have already been developed, including for product design (CAD systems), software products for technological production (CAPP systems), enterprise resource planning (ERP), advanced planning & scheduling (APS), manufacturing executing system (MES), quality assurance (QA-systems) [3]. However, the more systems and software products are used in the enterprise, the more problems arise in the organization of communications and the provision of reliable and timely information flows.

An automated production planning system based on information about the composition of products and of technological production processes makes stringent requirements to the quality and timeliness of design and technological documentation, this data is also the basis for production plans calculations. The absence or incompleteness of such information can be a serious problem for production planning, which may even require a review of the methodology and tools for calculating production plans.

According to the authors of the article, the question of timeliness and completeness of data is especially important for the engineering enterprises with design and production according to individual customer requirements, where the process of preparing the design and construction documentation is carried out practically throughout the entire production cycle. In this case, most of the composition of the product is repeated to some extent or can be attributed to a certain class of produced parts or assemblies only by the experienced employee or a production worker, but it is difficult to be identified by the available information systems. At large enterprises, where the size of the production plans consists of tens and hundreds of thousands of operations, the dimension of the task further aggravates the situation.

Bearing in mind the above, the currently known technologies for working with large data [4] and recent breakthroughs in the field of artificial intelligence [5], the authors of the research came to the following conclusion: the inadequacy and untimeliness of information about the technological process
for the purposes of production planning can be compensated or completely excluded with the help of already developed and proven methods of artificial intelligence (machine translation in particular) [6,7].

2. Methodology

The first part of the work is practical and based on the implementation projects in three large machine-building holdings. The field of activity of the first company is the production of downhole equipment for the oil and gas industry. The specificity of production lies in the fact that due to different indicators inside well sites at different oil fields, every time one has to develop or refine its products. The second enterprise produces transformers for various hydroelectric power stations, which also have different characteristics, so developers have to make a large amount changes in the technological documentation. The third company is one of the leaders in the Russian market for the development and production of power and electrical equipment for the oil and gas, metallurgical and chemical industries [8]. The holding also develops and manufactures equipment for the power industry and the power grid complex.

The following methods were used for the research:

- questioning of stakeholders on the part of the customer. For this purpose, specialized questionnaires were developed for each unit. In the questionnaires, key users noted information about job responsibilities and types of documents processed. Completed questionnaires were processed by an expert in the field of automation of industrial enterprises;
- study of production documentation: technological processes, route maps, product specifications and other regulatory and reference information;
- studying software products used for the design and planning of technological processes;
- interviewing stakeholders on the part of the customer. The purpose of the interview is to cover the issues that arose after processing the questionnaire. Interview is the final touch for describing the current business process.
- Focus group discussion was used to build a future enterprise model. Focus groups discussed the problematic issues of automation, proposals on adjusting the business processes that the responsible party put forward.

In the second part of the research, a study of scientific literature devoted to the problems of neural networks took place.

The development of a new product is considered as a task. The product consists of several large assembly units, which in turn consist of smaller assembly units, etc. Each unit "explodes" until we reach the purchased materials. Thus, the specification of our future product can contain up to several thousand parts produced. It should be understood that each part has its own technological process, which can contain up to 30 operations.

During the interviewing and questioning it was revealed that during the development of new types of products, a part of the detail can be similar to those, which were previously produced, some of the details can be developed from the beginning, and some of the details may have similar characteristics. When the design drawings are prepared, it is necessary to develop the documentation of the technological processes.

Modern CAPP systems allow automatic selection of technological processes for identical (previously produced details. In this part the process is already automated, but for details that are developed from the beginning or have similar characteristics, this technique is not applicable.

During the discussions in the focus groups it was revealed that often in the developed from the beginning or modified details, the technological processes will be similar or identical for the already developed products, but the existing technology selection process will not offer the technical process, since this detail has differences from those already existing in information system.

The study of research papers devoted to such problems did not reveal a developed solution for optimizing the process of automating the selection of technological processes according to the available list of details. From the point of view of the task posed articles in the field of artificial intelligence turns out to be unexpectedly interesting, exactly the machine translation of foreign languages and machine description of images. [9]

The enormous success of the Internet search leader Google in translating texts from one language to another, (as well as other participants in the scientific and applied community in the field of
machine translation) has already proved the effectiveness of machine learning methods for translation (translation of meaning) from one language to another (from one set of symbols into another)[1], [2], and for the verbal description of the images (the translation of the meaning from one set of symbols (images and their combinations in the picture) to another (text)), as well as the verbal description of the video images (the transmission of the meaning of the pictures taking into account their changes in time).

In these quite different applied problems, in our opinion, there is a general property. The understanding of this property prompted us to the idea of its possible use for the problem described above: all these cases are similar in one fundamental property - people are trying to describe the same essence in different ways. In translation, these are two different languages. In the description of a picture and video it is a translation from the language of images, which we naturally perceive by one of our six senses, into another form of meaning transfer - words (the alphabetic display). In our case, on the one hand, we describe some output product through a set of its parts (the table is something that consists of a lid and four legs), and on the other hand, the table is something that we get when we perform a set of actions. "Operation 1: Take the table top; put it on the bench upside down. Operation 2 Take the leg of the table and screw it into one of the holes in the bottom of the table top. Operation 3-5 Repeat step 2 for the remaining table legs by placing them in the remaining free holes."

Thus, the observation described above allows us to put forward a hypothesis that by applying methods similar to machine translation techniques to the problem of auto-selection of the technological process, we can achieve the desired goal (automatic determination of the technological process of manufacturing the product according to the composition of its components).

To solve this problem, an attempt to adopt machine translation method is described in current study. Vector space models (VSMs) represent (embed) words in a continuous vector space where semantically similar words are mapped to nearby points ('are embedded nearby each other') [2]. Such a model may be interesting and can allow taking into account the cases where the similarity of the products composition takes place. Besides, it can be quite effective, when the technological processes are identical or so similar, that might be considered as identical.

Another model that is actively used in machine translation is a model Word2vec. There are two versions of this model CBOW and Skip-Gram [2]. Both models are based on the principle of joint occurrence of words and the possibility of predicting the probability of the appearance of a word, based on the context of its appearance. However, in the case of the existence of critical dependencies between words in the text (the sequence, the presence of related words at a considerable distance (the number of other words in the text) between them), the approaches listed above prove to be ineffective, in contrast to the one used lately and a neural-based Sequence-to-sequence (seq2seq) method.

In general, seq2seq is a sequence of two mechanisms: an encoder and a decoder and a number of auxiliary mechanisms, such as: attention mechanism [2], the mechanism for optimizing the search for the most likely answer in deciphering (beam-search).

Encoder-decoder architecture – example of a general approach for NMT. An encoder converts a source sentence into a "meaning" vector which is passed through a decoder to produce a translation [10].
3. Results
Let’s consider the concept of the proposed solution using a simple example.

In the MES of the enterprise for a few years, a sufficient large amount of data on the products produced has accumulated. At the same time, we can obtain accurate names for the parts produced, their characteristics, such as: the outer and inner diameter of the finished part, the length of the finished part, the steel grade from which it is made, the standard length, the outer and inner diameter of the workpiece from which the part is made. For convenience, these data are tabulated for three "similar" parts on each other:

Table 1. Hypothetical specification.

| Parameter     | Part TL 1 | Part TL 1-2 | Part TD 2-1 |
|---------------|-----------|-------------|-------------|
| Outer diameter| 25 mm     | 25 mm       | 24 mm       |
| Inner diameter| 20 mm     | 20 mm       | 18 mm       |
| Length        | 600 mm    | 600 mm      | 600 mm      |
| Round beam    | 1 unit    | 1 unit      | 1 unit      |
| Outer diameter| 27 mm     | 26 mm       | 26 mm       |
| Inner diameter| -         | 10 mm       | -           |
| Length        | 1200 mm   | 1200 mm     | 1400 mm     |
| Metal mark    | Steel MX-10 | Steel MX-10 | Steel M-35  |

In addition, since these parts have already been produced, information about the technology of their production is available to us at the level of abstraction, which necessary for the production planning. Despite some difference in the parameters of the parts Part TL 1, Part TL 1-2, the details of the composition, the order and the time of execution of technological operations for them are identical. While for the Part TD 2-1 the composition and the order of operations are identical to the previous ones, (in this case, the main reason for the differences are the properties of the material, the part is made from - the hardness of the steel.) The resistance of the material to the reverse affects the processing time.

Table 2. Map of technological processes.

| Operation number | Operation     | Time, min | Part TD 2-1 |
|------------------|---------------|-----------|-------------|
| 010              | Cutting       | 10        | 15          |
| 020              | Drilling      | 25        | 30          |
| 030              | NC turning    | 20        | 25          |
Let’s represent the data shown in a tabular form in a slightly different form, namely as a body of parallel texts, as it is done in solving the problems of machine translation and other similar problems [1].

| Part_TL 1 | Part_TL 1-2 | Part_TD 2-1 |
|-----------|-------------|-------------|
| 25_mm 20_mm 600_mm Round beam 27_mm 1200_mm Steel_MX-10 | 25_mm 20_mm 600_mm Round beam 26_mm 10_mm 1200_mm Steel MX-10 | 24_mm 18_mm 600_mm Round beam 26_mm 1400_mm Steel M-35 |
| Cutting Drilling NC_turning Metal work QC | Cutting Drilling NC_turning Metal work QC | Cutting Drilling NC_turning Metal work QC |

As shown in the example, in most cases, the initial data for the task will be stored in a table format. In the framework of the ETL standard for machine learning tasks, we will have to perform additional actions to bring the data to the original form for the machine translation (the body of parallel texts). First, we need to present a set of procurement features in the form of a list of values with ordering, the numerical values of the measure units and their notation are represented in the form of words (by linking through the underlined). Second, we need to represent the sequence of operations, ordered by ascending number of operation in process technology, while leaving behind the numbers themselves and the execution time.

The first column of the table obtained (product description in the design view) can be interpreted as texts in the original language, the second column (product description in the technological view) as texts in the translation language.

Having performed such a transformation, we get a set of data standard for the machine translation task seq2seq, and then we can apply the technique similarly to its application to texts in natural languages (in fact our descriptions are text in natural languages, even in one natural language, but in different language subsets of the dictionary representation).

Proceeding from what has been said above, the authors of the article hypothesize that the task of automating a process based on a known composition of an assembly or a set of characteristics of a part can be logically reduced to the task of translating text from one language to another or a derivative of the task of text description of the image [12]. Accordingly, the same decision methods can be applied to the task of auto-selection of technical processes as for machine translation or textual description of the image, such as, machine translation algorithms of the seq2seq type as described in [1] and software, implementing such algorithms [11-14].

4. Discussion
According to the data available to us, the hypothesis about the similarity of the problem of auto-selection of technical processes and the task of machine translation of texts has not been proposed before and is proposed by us based on our understanding of machine translation technologies and automated text description of images, as well as it is based on our experience in automation of manufacturing enterprises based on PLM functionality, ERP, APS, MES.

In this regard, we are very interested in the opinion of the expert community on the formulation of the problem and the proposed method for solving it, it would be especially interesting to hear about
the results of the practical implementation of the ideas put forward by us, for example, by popular platform Tensorflow [8] and its specialized library tf-seq2seq [9].

In addition, we see the possibility of predicting the operation time, after determining the composition of operations. Time of operation can be predicted by ML methods - standard classification approaches.

Table 4. Example of automated time calculation

| Operation number | Operation   | Time, min |
|------------------|-------------|-----------|
| 010              | Cutting     | 10        |
| 020              | Drilling    | 25        |
| 030              | NC turning  | 20        |
| 040              | Metal work  | 10        |
| 045              | QC          | 5         |

5. Conclusion

In the current research, the task of auto-selection of technological processes during the development of a new product was formulated, advanced machine translation methods were considered, and an assumption was made about the logical similarity of the problem of auto-selection of the technological process and the translation of the text, as well as the proposal for the use of machine translation technologies for solving the problem of auto-selection of technological processes.

In the case of confirmation of the formulated hypothesis and solution of the problem by machine translation methods, it is possible to expect a significant reduction in the labor intensity of the development of technological processes, which may result in a positive economic effect (increase in labor productivity and a reduction in the production cycle of the order).

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