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CONTROL, ROBOTICS AND INFORMATICS

Towards mass customization: automatic processing of orders for residential shipping containers – a case study example

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Abstract. Along with changes in customer expectations, the process of ordering a house, especially one built with the most modern technology from prefabricated HQ 40-foot shipping containers, should take place in an atmosphere of free-flowing, customer-friendly conversation. Therefore, it is important that the company producing such a solution has a tool supporting such offers and orders when producing personalized solutions. This article provides an original approach to the automatic processing of orders based on an example of orders for residential shipping containers, natural language processing and so-called premises developed. Our solution overcomes the usage of records of the conversations between the customer and the retailer, in order to precisely predict the variant required for the house ordered, also when providing optimal house recommendations and when supporting manufacturers throughout product design and production. The newly proposed approach examines such recorded conversations in the sale of residential shipping containers and the rationale developed, and then offers the automatic placement of an order. Moreover, the practical significance of the solution, thus proposed, was emphasized thanks to verification by a real residential ship container manufacturing company in Poland.

Key words: mass customization, residential shipping containers, natural language processing, automatic processing of orders.

1. INTRODUCTION

To meet the needs of customers and changes in the market, taking into account all unexpected occurrences, many companies need solutions that allow them to produce a product in specific variants, while maintaining a balance of costs, time and quality. In the context of home design and ordering, trends and market demands have also changed. Customers need good-quality homes as quickly as possible, in line with their needs. In the context of prefabricated buildings, managers of companies offering such houses need solutions to reduce design time and thus minimize costs.

Mass customization is a production strategy consisting in producing various product models while reducing production costs, in terms of the time needed to produce the goods, the tools, equipment and storage. Manufacturers, in line with this strategy, face numerous challenges: the maximum use of resources, expansion of the machine park and changes in the number of employees, while simultaneously improving the flexibility of production and working space [1, 2]. This type of production also requires producers to adapt to the requirements of individual customers and to build close relationships with them [3]. Therefore, the ability to implement production following the strategy of mass customization has been defined as a factor related to the assessment of a producer's ability to compete in a rapidly changing environment [4]. Moreover, effectiveness of transformation of the idea included in the product design into added value for the customer depends on the support from information solutions [5].

Looking at the development of the mass customization (MC) concept, in enterprises and modern solutions, enabling the automatic support of the ordering process dedicated to the customer's needs, this article proposes a solution, based on an analysis of the literature on the subject, supporting the work of the seller during free-flowing and frank conversations with the customer, created in order to automatically complete the residential shipping container order form and provide a personalized offer to the client during the conversation. This work has been conducted in collaboration with a manufacturer of residential shipping containers based in Poland.

The so-called "chat bots" are used to facilitate routine customer service queries [6–8]. While usually they take the form of text messages, due to the cost of implementation, with the help of which they ask questions and get answers from their users, they have a voice interface and try, ever more frequently, to simulate a conversation with a real person. This subgroup is called voicebots [9, 10]. Using natural language processing (NLP) and a conversation scenario, designed at the implementation stage, they are able to correctly and effectively acquire the knowledge necessary for continuing the contract or ser-

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vice [11, 12]. However, while today there are no technical restrictions as to the areas of their application, in some situations it is very difficult to convince customers to make decisions involving or associated with large amounts of money, based on a "conversation with a machine". In such situations, both the customer and the seller expect a personal exchange of information and precise confirmation of their intentions and final decisions. These types of processes certainly include the selection of a variant for a prefabricated house built using 40-foot shipping containers. The essence of this process is a personal conversation between the client and the consultant and a detailed analysis of their needs, expectations and opportunities. It is on this basis that final decisions are made, often involving significant expense. It is also worth remembering that many such meetings and discussions take place at the arrangement stage. Consultants in the "Shipping Container House" Manufacturing Company, based in Poland, take detailed notes at each meeting. It is also worth mentioning that many of these conversations are preliminary meetings with customers, or even just a presentations of opportunities, organized in order to learn about customer preferences. Currently, it is not possible to generate an offer in line with the customer's needs during the conversation with the customer. Subsequent analysis of the course of individual conversations is also time-consuming and, due to deficiencies in the notes, not very precise. While it is possible to use ready-made software, available in the market, in the case of conversation robots and the "step by step" [13–15] acquisition of knowledge, based on a pre-determined scenario, in the case of the analysis of previously collected material, researchers propose tools dedicated to solving specific problems [16–18].

According to [19], a chatbot can be viewed as a machine-based conversation tool that interacts with human users through conversation. This technology is applied in many industries in the context of customer services [20–22]. In [23], the researcher recognized chatbots as a significant technological trend in supporting customer service in the following industries: online banking , e-service agents for luxury brands, airline carriers; travel agencies; telecommunications; rail transport; furniture retailing; health insurance, mobile service, car rental, clothing companies, hotels; smartphones and clothing companies. According to [24], employing chatbots instead of human employees to realize service tasks is motivated by the development of the natural language processing technology. However, on the other hand, it is becoming increasingly apparent that customers are skeptical about interacting with chatbots. Clients believe that robots do not have the emotional skills required to perform intuitive tasks [25]. It is also visible that clients prefer contact with human employees to conduct the conversation [26]. Although the use of chatbot technology has grown significantly in the service industry, consumer requirements and expectations are not always simple and straightforward, and chatbots do not understand the information being communicated [27, 28].

Therefore, in this study, we assume that our approach is based on a conversation between the customer and a human employee, and then, with the aid of natural language processing and application of our developed premises, it is followed by automatic processing of orders for residential shipping containers. The underlying algorithms of this premises enable the automatic processing of a dialogue outline and conversation between customers and the seller in order to automatically indicate the order variant without having to enter data into another information system and/or make written notes. Compared with traditional chatbot technology with only functional features, our solution is equipped with additional relational elements, which can allow to generate the automatic preparation of an offer on the basis of a conversation between the seller and the client.

So, our study has focused on how we can support the seller's work in the process of preparing an offer and ordering the production of residential shipping containers in the mass customization strategy, based on individual customer requirements and on free-flowing conversation with the customer. An algorithm was developed that, using the premises defined by the seller, will allow a text recording of the conversation, obtained by using automatic speech recognition – ASR – to be classified according to the characteristics of the residential shipping container sought. Then, based on a telephone call or direct conversation between the seller and the customer, it is possible to automatically generate an offer for the house, using the order form shown in the real case study. Therefore, our solution proves competitive to an automated chatbot when selecting configurations is concerned.

This paper proposes a novel approach to the automatic preparation and ordering process for an offer of a residential shipping container, and is based on the application of ASR and NLP. The main contributions of the work can be summarized as follows:

- A new algorithm, based on the actual knowledge of the order process for a customized residence in the form of prefabricated HQ 40-foot shipping containers, and on the actual conversation with the client, enabling the automatic preparation of an offer.
- The approach presented involves ASR and NLP for the purposes of automatically completing the offer and the production order for the customer.
- A tool can be developed supporting the seller's work when preparing a customized residence in the form of prefabricated HQ 40-foot shipping containers.
- The approach developed is illustrated using a real-life case study of a customized residence made from prefabricated HQ 40-foot shipping containers.
- The proposed approach to the automatic preparation and ordering process was verified during 28 conversations for three steps and yields of 89.28% accuracy of identification.

2. MATERIALS AND METHODS

2.1. The ordering process for customizing a residence made from prefabricated HQ 40-foot shipping containers

The ordering process for customizing a residence made from prefabricated HQ 40-foot shipping containers is carried out in the form of a direct conversation between the customer and the seller. The purpose of this conversation is to gain knowledge about the customer's preferences regarding (1) the size of the residence, (2) the price level, and (3) the style in which it is to be arranged.

1. Sizes of residences made from prefabricated HQ 40-foot shipping containers:
   - A single-module variant with an area of 30 m2 designed for up to 2 people. This module includes a bathroom, a bedroom, a kitchenette and a small living area.
   - A three-module variant with an area of 60 m2 designed for up to 3 people. This module includes a bathroom, 2 bedrooms, a kitchenette, a living room and a hall. Due to its asymmetrical design, this variant is available in two architectural sub-variants: a left subvariant and a right subvariant.
   - A four-module variant with an area of 90 m2 designed for up to 4 people. This module includes 2 bathrooms, 3 bedrooms, a kitchen, a living room and a hall.
2. The price level per module and the standard of the residence made from prefabricated HQ 40-foot shipping containers:
   - Basic variant – in this case, the price of 1 module is 50 000 PLN and means that the finishing standard is known as a developer's standard with the exterior walls being lined with PVC siding.
   - Comfort option – in this case, the price of 1 module is 75 000 PLN and comes with the finishing standard known as finished, the exterior walls being a combination of structural plaster and PVC siding.
   - Premium variant – in this case, the price for 1 module is 100 000 PLN and comes with the finishing standard known as turnkey, the exterior walls being finished with a combination of structural plaster and composite boards.
3. Interior design style of residences made from prefabricated HQ 40-foot shipping containers: Scandinavian style of interior design, modern style of interior design, elegant style.

Figure 1 presents variants of prefabricated HQ 40-foot shipping containers.

As has already been indicated [16–18], it is necessary to build a solution the use of which can automatically help prepare a personalized offer for the purchase and production of a residential shipping container, based on a free-flowing conversation with the customer, which will allow the company to operate in accordance with the concept of Industry 4.0 in the MC strategy.

2.2. Overview of the proposed approach to the automatic ordering process for a residential shipping container

The solution (Fig. 2) assumes the use of a smartphone-class device, which, thanks to automatic speech recognition (ASR) mechanisms, allows the conversation to be directly replaced by text messaging. The recording obtained is then processed by the proprietary algorithm for the automatic analysis of statements, in order to confirm or reject the premises and indicate the choice of one of the many configurations or variants of the finished product, i.e. the residential shipping container.

Premises should be understood as having already been prepared by the seller or a "specialist" – a collection of words or short phrases that may indicate a particular technical or functional aspect of the residence being ordered. When this product becomes a ready-made residence, there are many such variants and their determining factors; therefore, for the purposes of this article, a simplified process for selecting residence variants was adopted, consisting of the 3 steps, described in the ordering process: step 1 – selection of the size of the residence, the final size depending on the number of modules used; step 2 – selection of the price level, in terms of 1 module and the standard of equipment in the final product; step 3 – choosing a variant for the style of interior design in the finished property.

The basis of this solution is a set of premises that should be confirmed so that the algorithm can indicate the options selected in each of the 3 steps. Premises take the form of single words or whole phrases. It was assumed that in the recording of natural language statements, analyzed with the use of an algorithm, individual words would be searched for and then the words, found in this way, would be extended to form phrases. The list of keywords is automatically updated, based on the content of the list of premises. For the purposes of this study, a set of premises for a simplified order for a property was prepared with the assistance of a specialist. As previously indicated, the order consists of 3 steps and in each of them, selection variants are possible. This gives 36 different variants of residences. The set of conditions prepared consists of 133 items (Fig. 3).

In the set shown in Fig. 3, two columns are relevant – the column marked as premise means a string of text that represents a premise, the occurrence of which, in the statement analyzed, increases the probability of choosing a given variant. The second relevant column is denoted as the frequency factor, where

(a) (b)

Fig. 1. Variants of prefabricated HQ 40-foot shipping containers, (a) 1 module, (b) 3 modules [29]

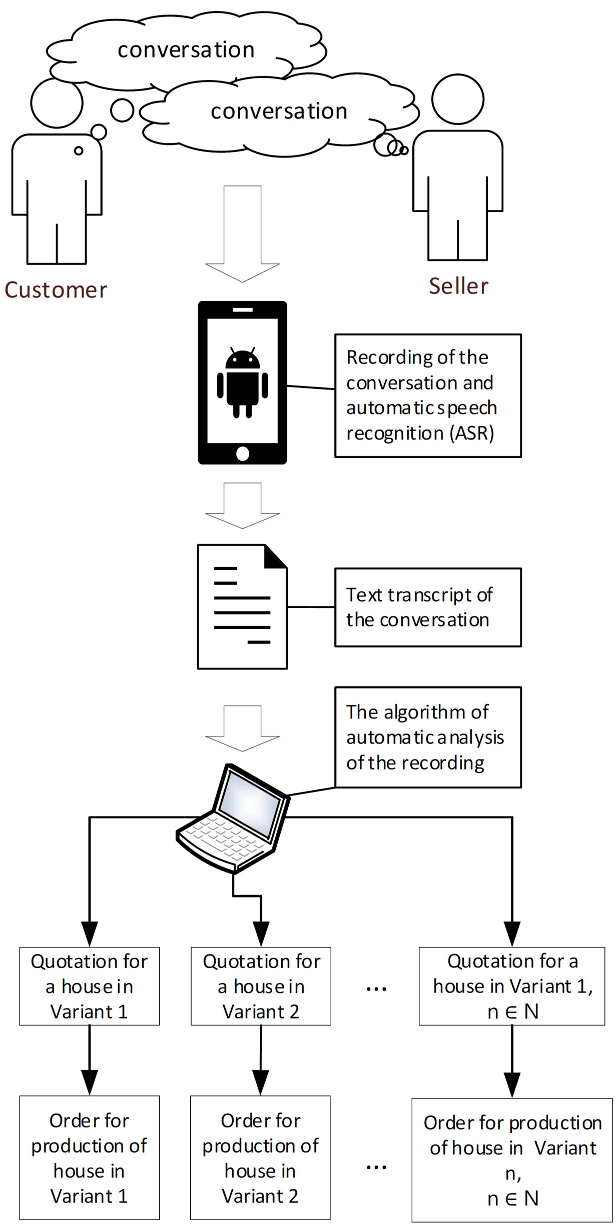


Fig. 2. Operating Model of the solution

variant_name	premise	frequency_factor
Single-module architectural variant	1 bathroom	3
Single-module architectural variant	2 people	2
Single-module architectural variant	kitchenette	3
Single-module architectural variant	single-module variant	1
Single-module architectural variant	living room	4
Single-module architectural variant	bathroom	3
Single-module architectural variant	30	1
Single-module architectural variant	smallest	1
Single-module architectural variant	1 day zone	3
Single-module architectural variant	1 person	4
Single-module architectural variant	1 bedroom	1
Single-module architectural variant	30 meters	1
Three-module right architectural variant	1 module	1
Three-module right architectural variant	day zone	3
Three-module right architectural variant	singlemodule	1
Three-module right architectural variant	person	4

Fig. 3. Selected part of the list of premises for each product variant

the values assigned to each premise can be seen. This value is determined automatically in our algorithm and means the number of instances of a given condition in all variants assigned to each of the steps. This coefficient allows the most likely customer decision regarding the choice of variant to be determined, according to the proposition that the greater its value, where the premise is applicable to more variants, the smaller the impact of this premise on the choice of the variant.

It is worth noting here that the same premise can be assigned to many variants; this is due to the fact that, for example, the 4-module variant can be lived in not only by 4 people, but also by 3 people or by only 2, which can also be changed and edited in the solution proposed (Fig. 4).

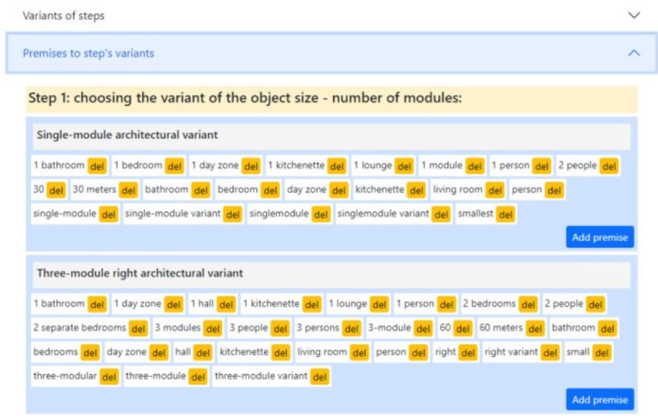


Fig. 4. Variant management window and corresponding premises

3. RESEARCH RESULTS

3.1. Algorithm for the automatic analysis of a statement

The automatic process of analyzing a conversation consists of two steps: (1) preliminary analysis of the recording of the conversation provided, and (2) designation of the most likely variants of choices in individual steps defining the order (please see below).

Algorithm 1: step 1

```
input data:  {recordOfTheConversation},
[arrayOfPremises]
initial assumption:
        [result] = [nonDefined]
[keywords] =
getSingleWordsFromPremises(arrayOfPremises)
let tokenizedWords =
word_tokenize(recordOfTheConversation)

for i=1 to length(keywords)
{
  for j= to length(tokenizedWords)
  {
  similarity =
wup_similarity(keywords[i],tokenizedWords[j])
  if (similarity==1)
    {
     result[i][keyword] = keywords[i]
```

```
     result[i][word] = tokenizedWords[j]
     result[i][similarity] = similarity
    }
  else
    {
     [arrayOfSynonyms] =
wordnet.synsets(tokenizedWords[j]).lemas.name()
     for k=1 to length(arrayOfSynonyms)
     if
(wup_similarity(keywords[i],arrayOfSynonyms[k])>0.9)
    {
     result[i][keyword] = keywords[i]
     result[i][word] = arrayOfSynonyms[k]
     result[i][similarity] = similarity
    }
   }
  }
}
output data:
        [result]
```

In this first step, two stages can be indicated.

Stage 1 – at this stage, the full-text recording of the conversation is divided into individual words, using the function of word_tokenise() from the NLTK (Natural Language Toolkit) of the Python Package [30]. This list, thus determined, is stored in the system database and, in addition to the word itself, its position in the text is also recorded.

Stage 2 – at this stage, the search for occurrences of previously determined keywords in the set of words found in the text is carried out. To this end, a semantic similarity level to all keywords is determined for each of these words. The wup_similarity () function, also from the Python Package of the NLTK library, was used to determine this similarity. This function uses the WordNet language corpus. WordNet is a lexical database for the English language. If the value of the similarity of the keyword compared is 1, it means that the occurrence of the keyword is confirmed, with the grammatical form of both compared words being irrelevant in this case. If not, synonyms of this word are established and the level of similarity is analogically determined for them. If the similarity level of any synonym exceeds 0.9, as determined by means of an experiment, the synonym also ends up as potentially similar to the list of keyword occurrences, stored in the database. Ultimately, the one with the highest value of this similarity is taken into account. Thanks to this, it is possible to find not only direct occurrences of keywords but also potential synonyms of their occurrences, which allows the effectiveness of their searches in the notation of statements to be increased in the natural language.

Algorithm 1: step 2

```
input data:   [arrayOfKeywordOccurrences] //result of
step 1
        [arrayOfPremises]

initial assumption:
        [result] = [nonDefined]
for each [premise] [in] [arrayOfPremises]
{
  [occurrencesOfPremises][premise] =
prepareOccurrencesOfPremise(premise,
arrayOfKeywordOccurrences)
}
for each variant
{
  [result][variant] =
variantMathingFactor([occurrencesOfPremises])
}
output data:
        [result]
```

In this step two stages can be distinguished:

Stage 1 – at this stage, the position of the occurrences of all premises assigned to individual variants is shown in the recording of the interview analyzed. In this case, the starting point is the position of the occurrences of individual keywords, or of their synonyms. For each premise, independent tables of the occurrence positions of all the keywords constituting this premise are determined, and then, on their basis, the table of the occurrence positions of the premise is determined, i.e. places where occurrences of the positions of individual keywords form a sequence consistent with the sequence of the words in the premise.

Stage 2 – at this stage, the number of occurrences of premises found, which have been assigned to individual decision variants for individual steps, is calculated and, on the basis of these quantities, the matching coefficient of individual variants is determined, this being the sum of the number of occurrences of individual premises for a given variant, where each of the elements of this sum is divided by the frequency coefficient, determined for a given premise.

$$\mathrm{Vmf}_i = \sum_{j=1}^{nmp} nop_j / rf_j\,, \tag{1}$$

where: Vmf_i – the i-th variant matching factor, where $i \in N$; nmp – the number of premises matched; nop_j – the number of occurrences of the premise where $j \in N$; rf_j – the frequency factor of the j-th premise 5, where $j \in N$.

The influence of the characteristics of premises for a given variant has a greater impact on the value of the matching coefficient than do the premises of a larger number of variants. The variant with the highest value of this coefficient is finally indicated as the most probable for a given step.

3.2. System for the automatic ordering process for a residential shipping container – a case study

This system consists of two co-operating WEB applications (Fig. 5).

The item marked in Fig. 5 as WEB Application I is the primary service that the system operator's web browser communicates with. It consists of an application, written in PHP, that handles web browser requests, stores and reads data from a related database and returns the results to the browser. The

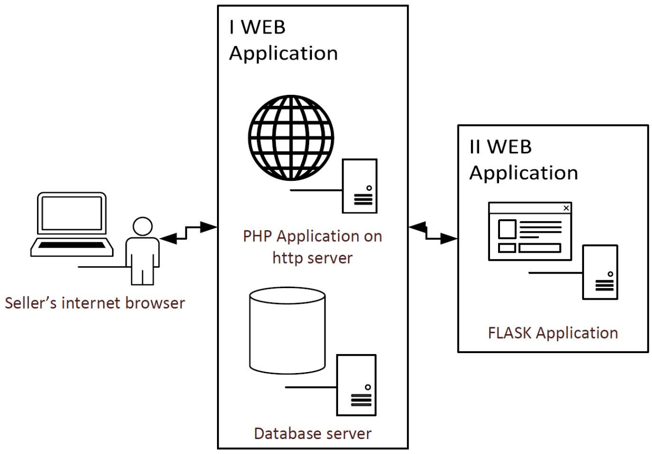
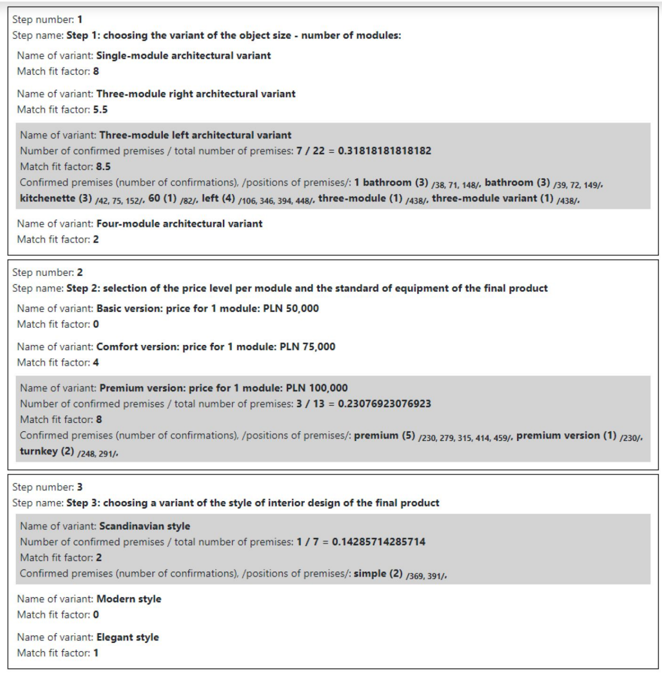


Fig. 5. Architecture of the automatic speech analysis module


Step number: **1**
Step name: **Step 1: choosing the variant of the object size - number of modules:**

Name of variant: **Single-module architectural variant**
Match fit factor: **8**

Name of variant: **Three-module right architectural variant**
Match fit factor: **5.5**

Name of variant: **Three-module left architectural variant**
Number of confirmed premises / total number of premises: **7 / 22 = 0.31818181818182**
Match fit factor: **8.5**
Confirmed premises (number of confirmations), /positions of premises/: **1 bathroom (3)** /38, 71, 148/, **bathroom (3)** /39, 72, 149/, **kitchenette (3)** /42, 75, 152/, **60 (1)** /82/, **left (4)** /106, 346, 394, 448/, **three-module (1)** /438/, **three-module variant (1)** /438/,

Name of variant: **Four-module architectural variant**
Match fit factor: **2**

Step number: **2**
Step name: **Step 2: selection of the price level per module and the standard of equipment of the final product**

Name of variant: **Basic version: price for 1 module: PLN 50,000**
Match fit factor: **0**

Name of variant: **Comfort version: price for 1 module: PLN 75,000**
Match fit factor: **4**

Name of variant: **Premium version: price for 1 module: PLN 100,000**
Number of confirmed premises / total number of premises: **3 / 13 = 0.23076923076923**
Match fit factor: **8**
Confirmed premises (number of confirmations), /positions of premises/: **premium (5)** /230, 279, 315, 414, 459/, **premium version (1)** /230/, **turnkey (2)** /248, 291/,

Step number: **3**
Step name: **Step 3: choosing a variant of the style of interior design of the final product**

Name of variant: **Scandinavian style**
Number of confirmed premises / total number of premises: **1 / 7 = 0.14285714285714**
Match fit factor: **2**
Confirmed premises (number of confirmations), /positions of premises/: **simple (2)** /369, 391/,

Name of variant: **Modern style**
Match fit factor: **0**

Name of variant: **Elegant style**
Match fit factor: **1**

Fig. 6. Result of analysis of a sample recording of a conversation

database stores orders, along with their full content and all the established parameters based upon them. The database also stores all system configuration data, such as definitions of the steps of an order, definitions of individual variants and definitions of the premises assigned to them. To prepare the final result, it uses the services offered by the application marked as WEB Application II, which takes the form of a microservice, prepared in the PYTHON language and launched using the FLASK framework. A section from a full-text recording of a sample conversation between the seller and the customer is presented below. This recording was obtained using a smartphone-class device with the Google Speech Api, provided by the Android operating system.

Step 1 is to choose the option of the size of the facility depending on the number of modules and the purpose for the maximum number of people variant No. 1 is a one-modular architectural variant containing 1 bathroom 1 bedroom kitchenette living area it has 30 square meters of space and is intended for a maximum of two people The second architectural variant is the 3 modular variant containing 1 bathroom 2 bedrooms kitchenette living room hall the whole has 60 square meters of space and is intended for a maximum of 3 people living in the 3 modular variant has 2 right and left sub-variants The third architectural variant is the 4 modular variant which includes 2 bathrooms 3 bedrooms kitchen living room hall has 90 square meters and is designed for a maximum of 4 people…

Figure 6 shows the result of an analysis of the recording of the above conversation.

As shown in Fig. 6, as a result of the operation of the system, the user is presented with a list of steps describing the order. For each step, a list of all deciding variants that have been defined for it, along with the variant-matching factor established for the premises defined, is presented. In addition, information regarding the number of premises confirmed is displayed for the variant with the highest value of this coefficient as is also the number of occurrences of each of them, as well as the items in the text where they were found. The application allows the contents of the recorded conversation to be viewed, including the numbers of individual words, in order to facilitate verification.

The example shown in Fig. 6 shows that the solution in question correctly indicates the selected variant of the finished product. Actually, the customer chose a left-hand, 3-module variant, finished in the Scandinavian style and in the premium standard. On this basis, it is possible to automatically generate an offer for a customer for a house along with orders for production. The solution correctly indicates the selected variant of the finished product.

3.3. Verification of the system for the automatic ordering process for a residential shipping container

Research experiments were planned and performed to verify the solution being presented. In the first step, 28 conversations with clients were prepared in consultation with the employees of a manufacturer of residential shipping containers. The company operates in the Polish market; therefore the conversations were conducted in Polish. Our solution uses the English language corpus for analysis, so this is why the Google Translate tool was used to automatically translate the content of the conversations from Polish into English. Of course, such a solution does not allow for the achievement of high-quality translations, but from the point of view of the conducted experiments, it was sufficient. Next, the employees of the residential shipping containers manufacturer read the English-language versions of the planned conversations, broken down into roles, simulating the actual conversation. These conversations were analyzed on an ongoing basis using the Google Web Speech API tools, thanks to which their text representation was obtained. There were minor gaps in the records obtained, which may be due to not always correct pronunciation of employees in English. These shortcomings, however, did not affect the further course of the research experiment.

Conversations 1–28 were developed under certain assumptions (Appendix 1). The results of the experiments are presented in Table 1.

Table 1
Results of the tests

Conversations	Step 1		Step 2		Step 3	
	Expected variant	Acquired variant	Expected variant	Acquired variant	Expected variant	Acquired variant
1	v1	v1	v5	v5	–	–
2	v3	v3	v5	v5	–	–
3	v4	v4	v5	v5	–	–
4	v1	v1	v6	v6	–	–
5	v2	v2	v6	v6	–	–
6	v4	v4	v6	v6	–	–
7	v1	v1	v7	v7	v8	v8
8	v2	v2	v7	v7	v9	v9
9	v4	v4	v7	v7	v10	v10
10	v1	v1	v5	v5	–	–
11	v3	v2/3	v5	v5	–	–
12	v4	v4	v7	v7	v10	v10
13	v4	v4	v7	v7	v10	v10
14	v2	v2	v7	v7	v8	v9
15	v4	v2	v7	v7	v8	v8
16	v4	v4	v7	v7	v8	v10
17	v4	v2	v7	v7	v10	v9
18	v4	v4	v7	v7	v10	v9/10
19	v4	v4	v7	v7	v10	v9
20	v4	v4	v7	v7	v10	v10
21	v4	v4	v7	v7	v8	v8
22	v4	v4	v7	v7	v8	v10
23	v4	v4	v5	v5	–	–
24	v4	v4	v7	v7	v10	v10
25	v1	v1	v7	v7	v8	v8
26	v3	v3	v6	v6	–	–
27	v3	v3	v5	v6	–	–
28	v4	v4	v7	v7	v10	v10

where: variants (v) are marked with the following numbers, respectively: step 1: v1 – single-module, v2 – three-module (right), v3 – three-module (left), v4 – four-module; step 2 (the price level per module): v5 – basic, v6 – comfort, v7 – premium; step 3 (design): v8 – Scandinavian style, v9 – modern, v10 – elegant.

Our proposed approach to the automatic preparation and ordering process was verified on 28 conversations for three steps with yields of 89.28% accuracy of identification.

3.4. Efficiency of the system for the automatic ordering process for a residential shipping container

The three scenarios for simulation tests were planned and performed to assess the presented solution based on the 28 conversations (section 3.3).

The first scenario: The "developed system" prepares the order.

It is assumed that the developed system will be installed on a personal computer with parameters corresponding to a laptop-class device. Therefore, the virtual machine was prepared in order to conduct the simulation tests in which the amount of RAM was limited to 4GB and the number of available processor cores to 2. A local WWW server was launched on this machine with a PHP interpreter and a Python runtime environment. The simulation tests were examined for the total system operation time during the analysis of individual records, with an accuracy of 1 second.

The second scenario: the "experienced employee"' prepares the order. The employee analyzes the conversation with the client and fills in a questionnaire prepared using the Google Forms tool with the Form Timer extension, which allowed for precise determination of the time required to complete the form. This time was also measured with an accuracy of 1 second.

The third scenario: the "employee"' prepares the order. The employee analyzes the conversation with the client and fills in a questionnaire prepared using the Google Forms tool with the Form Timer extension, which allowed for precise determination of the time required to complete the form. Additionally, this person uses the auxiliary list, which collected the premises related to the individual procurement subvariants. The results of the simulation tests are presented in Table 2

Table 2
Results of the simulations

Conversations	Word count	Scenario 1 analysis time	Scenario 2 analysis time	Scenario 3 analysis time
1	62	00:00:24	00:00:55	00:01:21
2	94	00:00:26	00:00:36	00:02:09
3	60	00:00:25	00:00:41	00:01:16
4	46	00:00:20	00:00:43	00:01:13
5	95	00:00:33	00:01:17	00:02:21
6	81	00:00:26	00:00:46	00:01:13
7	60	00:00:25	00:00:39	00:00:55
8	119	00:00:32	00:00:59	00:02:00
9	89	00:00:23	00:00:36	00:01:42
10	88	00:00:28	00:00:53	00:01:03
11	88	00:00:33	00:00:36	00:01:40
12	105	00:00:28	00:00:59	00:01:40
13	100	00:00:25	00:00:45	00:00:51
14	140	00:00:30	00:00:56	00:01:37
15	107	00:00:42	00:00:42	00:01:10

Table 2 [cont.]

Conver-sations	Word count	Scenario 1 analysis time	Scenario 2 analysis time	Scenario 3 analysis time
16	102	00:00:35	00:00:47	00:00:51
17	147	00:00:42	00:01:25	00:02:13
18	131	00:00:37	00:00:53	00:01:12
19	128	00:00:40	00:00:57	00:01:00
20	146	00:00:43	00:00:51	00:01:02
21	143	00:00:42	00:00:52	00:01:05
22	148	00:00:41	00:00:47	00:01:43
23	143	00:00:43	00:01:00	00:01:31
24	149	00:00:42	00:01:13	00:01:48
25	140	00:00:33	00:00:53	00:01:17
26	131	00:00:32	00:00:46	00:01:12
27	162	00:00:42	00:01:03	00:01:35
28	180	00:00:41	00:01:22	00:02:02

The times for the three scenarios presented in Table 2 are summarized in Fig. 7a, b. The graph in Fig. 7 has been divided into two parts to increase its readability.

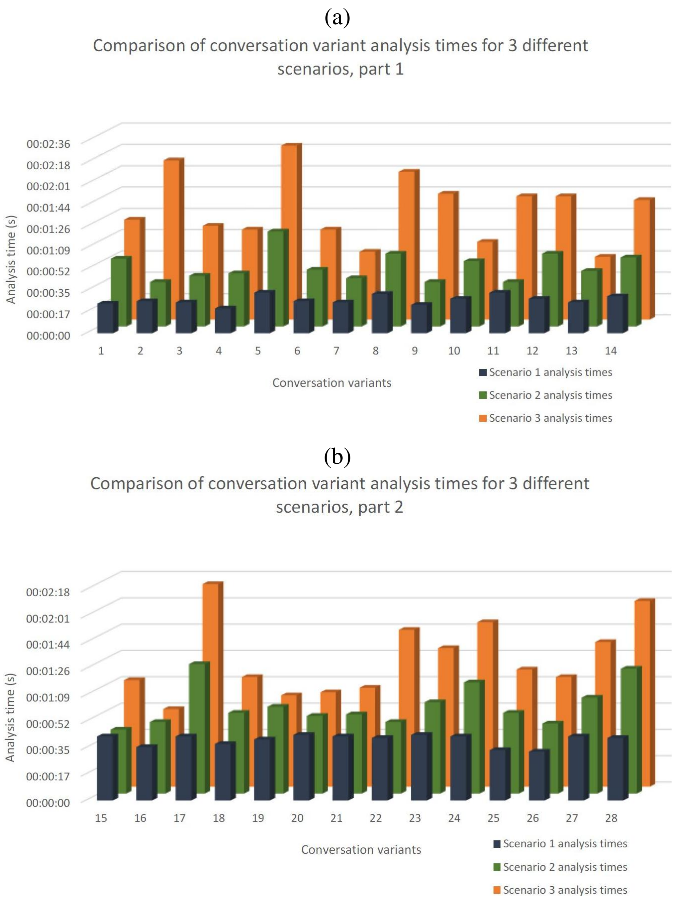


Fig. 7. Result of simulation tests, (a) variants of conversations with numbers from 1 to 14, (b) variants of conversations with numbers from 15 to 28

The results presented in Fig. 7 for each of the 28 variants of conversation indicate that the time of conversation analysis is shorter when the developed system (section 3A, B) is used than when such analysis is provided by an employee and is not supported by the system. The data presented in Fig. 7 show that the time of each conversation analysis supported by the system depends on the time of the recording, not on the level of complexity of the analyzed conversation. Therefore, it should be assumed that the use of the presented solution in the cases other than those discussed above, especially when the number of variants of products or services will be much greater, will allow for even greater time savings compared to the analysis performed personally by an employee.

4. DISCUSSION

The proposed approach was presented and verified based on the example of the ordering process for residential shipping containers, in order to automate the process while at the same time providing the customer with the appropriate tool to support the decision to invest. However, our approach can be treated as the reproducible method. The basis of this solution is a set of premises that should be confirmed so that the algorithm can indicate the options selected in each of the three steps. So, in another case of application of our solution, the individual steps of the orders and the premises indicating the choice of individual variants of steps should be defined according to specification of other orders.

Table 2 summarizes the main features that distinguish the proposed work from existing, related works. It enriches the discussion with a rapid overview of the main thesis of this paper, with respect to the state-of-the-art analyzed. Going into more detail, Table 1 gives information on related work about: a) applying NLP to solutions supporting order processing in production, within a strategy of mass customization, b) using the modelling approach, c) using the model in the industry, and d) the originality of the model. To the best of our knowledge – and as stated in an analysis of the literature, no similar approach, based on ASR and NLP, and supporting the process for the automatic ordering of residential shipping containers, was found.

Our research results can be treated as the “lessons learnt” in the context of the possibility of implementing a new solution supporting the work of employees within a sales department within a manufacturing facility when producing personalized solutions. The system proposed enables automatic indication of the order variant without having to enter data into another information system and/or make written notes by the seller. The proposed solution will allow the managers operating according to mass customization, where each production order is different, to increase the efficiency of processing of individualized orders thanks to:

- shortening the time of analyzing the conversation between the customer and the seller (Table 2).
- elimination of errors in the preparation of the offer for the client.
- elimination of errors in the preparation of the order for production.

Table 3
Results of the state-of-the-art analysis

Use of NLP in the production of mass customization	Using the Model	Industry	Novelty	Ref.
Material and cost estimation of a customized product namely: electrical distribution boards	Description of the product's characteristics, as provided by the customer A set of 1 347 different switchgear variants (from 3 years of production), each of which is described by 843 attributes, usage of deep neural network	yes	Value equal to the quantity of that component according to the bill of materials for electrical distribution boards	32
Obtaining the user's requirements from on-line reviews	Language model BERT (Bidirectional Encoder Representations from Transformers)	yes	Methodology for the automated and large-scale obtainment of attribute-level user requirements	33
Means of facilitating product customization	Requirements-based, configuration mechanism based on text embeddings and multi-layer perceptron	no	Mapping customer requirements into product configurations using a multi-layer perceptron	34
Defining the requirements for the purchase of large and complex power transformers	Chatbot which uses a database of 1 272 questions	yes	Chatbot + visualization 3D	35
Digital shop floor management, based on NLP	Using NLP for document clustering: a digital ticket system for shop floor issues to find the most frequent terms and intersections	yes	Procedure to identify the most common employee problems	36
Identification of the product variant	Opinions regarding the product; keyword classification, using the hierarchical attention network	yes	Requirement-based configurators for finding satisfactory products	37
Modelling customers' emotional satisfaction	Cluster customers through the Kansei perspective	no	Suggestions for manufacturers to make precise decisions when launching new products	38
Establishing the product variant and ordering residential shipping containers	Recordings customer conversations with the seller, regarding the ordering process for a residential shipping container and using the rationale agreed upon for selecting the particular type of residential container required	yes	Automatic indication of the variant of the residential shipping container, based on the customer's comments and the automatic issuing of an offer and order for production	*This paper*

These benefits of the system proposed were demonstrated in the analyzed case (see Table 1 and Table 2). Based on the presented case study, a new system was developed to support the seller's work in the process of preparing the offer and production order of residential shipping containers in the mass customization strategy, based on individual customer requirements and on free-flowing conversation with the customer. In order to demonstrate universality and reproducibility of our solution, the three main stages for the preparation of this system for another manufacturing company operating in the strategy of mass customization was developed:

Stage 1: Define all steps in the processing of orders.

Stage 2: Define individual variants according to each step in the processing of orders.

Stage 3: Define the set of premises indicating each individual variant.

The presented solution has an obvious limitation, strictly related to the case study analyzed. It is built on a knowledge base, which currently includes only elements related to the selection process regarding the different types of residences available, which, in turn, was created based on the 3 steps described in the ordering process. Next, based on the results of the research experiments (section 3.3), it is needed to add to the developed algorithm the rules of searching for expressions in statements that unambiguously support or negate previously established premises. In consequence, the basic rationale for selecting the required variant of the house will be expanded. In addition, we plan to integrate the proposed solution with an ERP system, supporting the current operations of manufacturers of residential shipping containers.

In further work, it will be necessary to expand the knowledge base and then implement machine learning (ML) techniques in order to classify the designated keywords for building the rationale. We know that there is great demand for using ML in the area of mechanical engineering in Industry 4.0 problem solving [31].

5. CONCLUSIONS

The production and sale of modular houses built from shipping containers has only been in operation for a year and its selectivity means that only a small number of orders are produced annually, thus forcing us to use the knowledge of specialists to prepare 136 rationales indicating the individual variants of the container house ordered. However, if the data collected from the statements is sufficiently comprehensive, it will be possible to use machine learning tools to automate the definition and create the principles. It is particularly important for the company's offer to be constantly developed and, consequently, for the number of potential variants of the houses thus ordered to grow rapidly along with the number of customers.

APPENDIX

Terms and conditions for conversations 1–28 included in Table 1.

- Conversations 1–9 are situations when the customer knows what they want, and the seller does not try to convince they of anything, clarifying the facts at most.
- Conversations 10–13 are examples in which the customer knows what they want but the seller tries to convince them to change one aspect.
- Conversation 14 is a case when the seller proposes changes to two issues – both are unambiguous and rejected.
- Conversations 15 and 16 are repeated, this time effective, attempts to change the client's decision. The client expresses their acceptance directly or indirectly.
- Conversation 17 is an effective attempt to change the client's decision in two aspects. The customer clearly confirms the acceptance of the proposal.
- Conversations 18 and 19: the customer is not sure about 1 issue, the seller accepts their other choices and proposes a solution that is directly or indirectly accepted.
- Conversation 20: in this case the customer is not sure about 1 issue – the seller offers them a solution, the customer accepts it, the seller tries to change 1 of the customer's previous decisions – unsuccessfully.
- Conversation 21: the course of the conversation is similar to conversations 21 and 22 – but in this case the attempt made by the seller is more effective. The client expresses their final decision directly and indirectly.
- Conversation 23: the customer is not sure about 1 issue, the seller offers them a solution, the customer accepts it, the seller tries to change 2 aspects, unsuccessfully.
- Conversation 24: the customer is not sure about 1 issue, the seller offers them a solution, the customer accepts it, the seller tries to change 2 aspects effectively.
- Conversation 25: the customer is not sure about 2 issues, the seller offers them a solution, the customer accepts it, the seller agrees with the customer on 3 issues.
- Conversation 26: the customer is not sure about 3 issues, the seller offers them a solution, the customer accepts it.
- Conversation 27: the customer is not sure about 3 issues, the seller offers them a solution, the customer does not accept one of the two proposals. The seller proposes another option, the customer accepts it.
- Conversation 28: the customer is not sure about 3 issues, the seller offers them a solution, the customer accepts one, initially does not accept the other two. The seller proposes other options, the customer accepts them.

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