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APPLYING BOX-BEHNKEN DESIGN TO RESEARCH VOICE CONTROL AUTOMATIC LIGHTING SYSTEMS

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Abstract. *The paper presents the results of an experimental study of a voice control system for smart home elements, implemented on the basis of the WeMos D1 mini microcontroller module using the Google Assistant voice assistant and a mobile application created in the MIT App Inventor environment. The purpose of the study was to determine the influence of the distance to the microphone, the sensitivity of the microphone, and the type of the user's voice on the efficiency of voice command recognition. The experimental planning was performed using the Box-Behnken method, which allowed obtaining statistically significant results with a minimum number of experiments. Analysis of the obtained data showed that the distance to the microphone and its sensitivity have the greatest impact on the accuracy of command recognition, while the type of voice is of secondary importance. The mathematical model built based on the obtained data was recognized as adequate according to the Cochrane, Student, and Fisher criteria. The obtained results can be used to configure and optimize similar IoT systems, as well as for further research in real acoustic environments.*

Keywords: smart home, WeMos D1 mini, Box-Behnken method, speech recognition, IoT

ZASTOSOWANIE MODELU BOX-BEHNKEN W BADANIACH NAD SYSTEMAMI AUTOMATYCZNEGO OŚWIETLENIA STEROWANYMI GŁOSEM

Streszczenie. *W artykule przedstawiono wyniki badań eksperymentalnych dotyczących systemu sterowania głosowego elementami inteligentnego domu, zrealizowanego w oparciu o moduł mikrokontrolera WeMos D1 mini z wykorzystaniem asystenta głosowego Google Assistant oraz aplikacji mobilnej stworzonej w środowisku MIT App Inventor. Celem badania było określenie wpływu odległości od mikrofonu, czułości mikrofonu oraz rodzaju głosu użytkownika na skuteczność rozpoznawania poleceń głosowych. Planowanie eksperymentalne przeprowadzono przy użyciu metody Boxa-Behnkena, co pozwoliło uzyskać statystycznie istotne wyniki przy minimalnej liczbie eksperymentów. Analiza uzyskanych danych wykazała, że odległość od mikrofonu oraz jego czułość mają największy wpływ na dokładność rozpoznawania poleceń, natomiast rodzaj głosu ma znaczenie drugorzędne. Model matematyczny zbudowany na podstawie uzyskanych danych został uznany za adekwatny zgodnie z kryteriami Cochrane'a, Studenta i Fishera. Uzyskane wyniki mogą zostać wykorzystane do konfiguracji i optymalizacji podobnych systemów IoT, a także do dalszych badań w rzeczywistych środowiskach akustycznych.*

Słowa kluczowe: inteligentny dom, WeMos D1 mini, metoda Box–Behnkena, rozpoznawanie mowy, IoT

Introduction

The rapid development of information and communication technologies and microprocessor technology contributes to the active implementation of the concept of a "smart home", which involves the integration of household devices into a single managed system. Modern solutions in this area are based on the use of the Internet of Things (IoT), which ensures interaction between various electronic modules, sensors, and actuators. According to research, the market for "smart home" systems is showing stable growth, and one of the key areas of its development is the development of convenient and reliable ways to control devices, among which voice control occupies a special place [13]. The voice interface of user interaction with technology offers several advantages, including the absence of physical contact with control elements, increased ease of use, and the possibility of integration with mobile devices and cloud services. However, the effectiveness of voice command recognition depends on many factors, such as the distance to the microphone, the acoustic characteristics of the room, the type and quality of the microphone, and the features of the user's voice. Optimization of these parameters allows you to increase the reliability and accuracy of the system, which is a relevant task for developers of IoT solutions [18]. Among modern hardware platforms for building control modules, microcontroller modules based on the ESP8266 chip, in particular the WeMos D1 mini board, have become widespread. Its advantages are a built-in Wi-Fi module, compact dimensions, compatibility with various sensors and actuators, as well as support for standard development interfaces. The combination of this hardware solution with a mobile application and cloud services (for example, Google Assistant) opens up the possibility of creating effective and scalable voice control systems [5]. The scientific papers present the results of research on individual aspects of voice control of IoT devices [15]. However, a comprehensive assessment of the impact of technical and technological factors on the accuracy of command recognition in systems based on WeMos D1 mini is practically absent. This necessitates the need for experimental studies to determine the optimal parameters of such systems.

The purpose of this research is to experimentally determine the impact of the distance to the microphone, microphone sensitivity, and user voice type on the efficiency of the voice control system for "smart home" elements based on the WeMos D1 mini Wi-Fi module using the Box-Behnken method.

1. Literature review

The concept of a "smart home" has become one of the key directions of development of modern information and communication technologies, based on the integration of household appliances, sensors, and actuators into a single intelligent network capable of providing comfort, energy efficiency, and security of the home. Among the various user interaction interfaces, voice control occupies a special place, which provides natural and intuitive communication with equipment. Due to the possibility of remote activation of commands, the absence of the need for physical contact with control elements, and high speed of interaction, voice interfaces are becoming an integral element of the IoT ecosystem [2].

The development of the hardware base has contributed to the active introduction of small-sized microcontroller platforms with built-in wireless communication modules, in particular based on the ESP8266 chip, into this area. One of the most common implementations of this class of devices is the WeMos D1 mini module, which combines compact dimensions, sufficient computing resources, and wide integration capabilities with sensors, actuators, and software [6].

The integration of voice control into smart home systems is often based on the use of cloud services such as Google Assistant or Amazon Alexa, which perform speech signal processing on remote servers. This approach provides high recognition accuracy due to the use of modern neural network algorithms, but at the same time, it requires a dependence on traffic stability and creates potential risks for data confidentiality. As an alternative, more and more attention is paid to local automatic speech recognition (ASR) systems that work without a network connection [4, 14].

The effectiveness of voice interfaces is influenced by numerous factors, among which the most significant are the distance between the user and the microphone, the level of background noise, the acoustic characteristics of the room, the sensitivity and quality of microphones, as well as individual voice characteristics. A number of studies indicate that the interaction of these parameters is complex, often nonlinear, which makes the application of mathematical modelling and experimental planning methods relevant. One of the most effective tools in this direction is the Box-Behnken technique, which allows minimizing the number of experiments and obtaining statistically significant results with an assessment of the effects of the interaction of factors [10, 11].

In parallel with the technical aspects, the issues of cybersecurity and protection of personal data in voice interfaces are actively studied. Researchers emphasize the need to implement protection against voice reproduction and spoofing attacks, the use of multi-factor authentication, and encryption of communication channels. Some works predict that the further development of voice control systems in the IoT field will be aimed at creating hybrid solutions that combine the advantages of cloud and local processing, provide adaptive noise reduction, take into account the context of use and the emotional state of the user, and are integrated with other interaction channels, such as gestures or visual recognition [7, 16].

Rapid mobile interface development tools, such as MIT App Inventor, are used to prototype IoT device control systems, providing visual programming and integration with speech recognition services. Despite limitations in functionality and performance, these environments allow you to significantly reduce development time and focus on experimental verification of engineering solutions [9].

Thus, the analysis of current research indicates that there is significant interest in the development and optimization of voice interfaces for controlling smart home elements, but comprehensive experimental work on assessing the impact of technical and technological parameters in the context of using WeMos D1 mini modules remains limited. This emphasizes the relevance of conducting research aimed at determining the optimal conditions for the functioning of such systems in real-life conditions.

2. Researches methodology

A convenient and common way to control smart devices is to use mobile devices running Android or IOS operating systems. Therefore, in general, the created control system should consist of two elements: the control part and the executive part. The control part is a mobile phone with the ability to connect to a Wi-Fi network and software. The executive part should consist of a microcontroller device with the ability to connect to a Wi-Fi network and switches that will close and open the electrical circuits of the load [17]. The WeMos D1 mini Wi-Fi module was chosen as the microcontroller device that will directly control the electrical switches (Fig. 1). The Box-Behnken design was chosen due to its ability to construct a second-order model with a reduced number of experiments compared to a full factorial design, while maintaining sufficient accuracy for nonlinear interaction analysis.

The WeMos D1 mini board is an analog of the NodeMCU v3 board based on the ESP8266 version of the ESP-12F chip. The main advantage of this module is that the WeMos D1 mini does not require an external microcontroller or another control device to operate, since in addition to the ESP-12F Wi-Fi module, it has a built-in 32-bit microcontroller with a clock frequency of 80 MHz, as well as a 4 MB flash memory chip. It also has smaller dimensions compared to other analogues. The WeMos D1 mini module is a fairly frequently used element when creating devices for the Internet of Things, as well as remote monitoring or control systems, various autonomous sensors, etc. [1, 20]. The board supports several options for working with Wi-Fi networks. It can be both a client of a Wi-Fi network and create a Wi-Fi access point itself. Therefore, using the WeMos D1 mini, compared to using a separate ESP8266, significantly simplifies the design, since this module already contains built-in components, such as a USB-UART converter, a linear voltage regulator, and contacts already wired to connectors with a standard pitch of 2.54 mm. The assignment of the WeMos D1 mini ports is shown in Figure 2.

Fig. 1. Appearance of WeMos D1 mini [12]

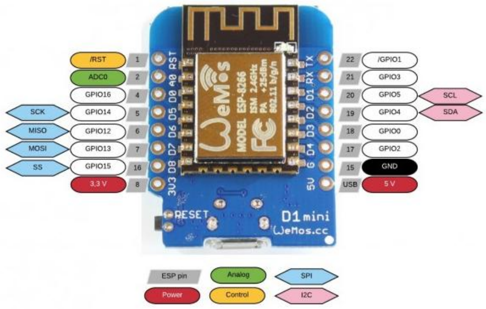

Fig. 2. WeMos D1 mini port assignments [3]

When creating this complex, it was determined that it should control four consumers of electrical energy. For switching the load circuits, two possible cases were considered. The first is the power supply of household appliances from the 220 V electrical network using a relay array with a low control voltage (Fig. 3a). The second is the power supply of LED strips or LED matrices using field-effect transistors (Fig. 3b).

a)

b)

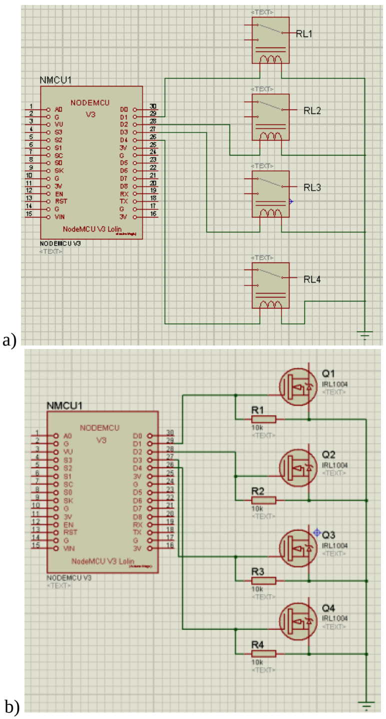

Fig. 3. Consumer connection diagrams: a) connection using electromagnetic relays, b) connection using field effect transistors

The software for this project was developed with the help of the MIT App Inventor service. This service is an integrated web application development environment. This environment allows you to create application software for two operating systems: Android and iOS [8]. It is free and has open source code, and is distributed under a dual license: Creative Commons Attribution ShareAlike 3.0 Unported and Apache 2.0. MIT App Inventor uses an intuitive graphical user interface, very similar to the Scratch and StarLogo programming languages. Although the service was created for educational purposes, currently, given its growing capabilities, it is increasingly used in cases where it is necessary to quickly develop a software product with minimal functionality for specific tasks. The software product was supposed to provide the ability to control several electric switches, both using voice commands using the Google Assistant service and by pressing the control buttons in the mobile application. In case of successful execution of the command, the application should inform with a voice message about the successful execution of the corresponding command [19]. The proposed mathematical model does not depend on the internal structure or algorithms of the cloud-based voice assistant. Instead, it describes the relationship between externally observable acoustic and system-level parameters (such as distance, microphone sensitivity, noise level, and voice type) and the recognition outcome. Although the internal algorithms of cloud-based voice assistants may evolve over time, the physical and acoustic parameters considered in this study remain invariant, which ensures the structural stability of the proposed model. Potential changes in recognition accuracy caused by future updates of the cloud service may lead to numerical shifts in model coefficients, while the functional form and identified parameter interactions are expected to remain valid.

For each electric key, there are two buttons on the screen opposite their identifiers: "ON" and "OFF". To call the voice assistant, there is a "Speech Text" element on the working field. The result of developing the graphic layout of the program is shown in Figure 4.

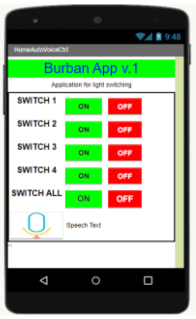

Fig. 4. Control program layout

This layout involves controlling four consumers with identifiers "SWITCH 1", "SWITCH 2", "SWITCH 3", and "SWITCH 4". Turning on "SWITCH 1" is done by pressing the "ON" button or entering the voice command "Turn on switch one". Accordingly, to turn off "SWITCH 1", you need to press the "OFF" button or enter the voice command "Turn off switch one". Turning on and off "SWITCH 2", "SWITCH 3", and "SWITCH 4" is done similarly. The "Speech Text" button is used to enter voice commands. When it is pressed, the Google Assistant voice assistant is called, which performs voice recognition and allows you to get the value of the corresponding command.

The developed control system supports 10 different voice commands. We considered presenting all possible command variants as one test. That is, the maximum value of the result will be 10, and the minimum zero.

Three different factors were varied in the study: distance from the user to the microphone, different voices, and different microphones. According to the Box-Behnken method, three levels of variation of the factors were initially selected. The factors are: distance, microphone sensitivity, and voice. The levels of variation of each factor are given in the factor coding Table 1.

Table 1. Coding of the experiment factors

Factors		Level of variation			Variation interval
Natural view	Coded view	-1	0	+1	
L, m	x_1	0.5	1	1.5	0.5
M_0, dB	x_2	-46	-52	-58	6
voice	x_3	male	female	children's	1

According to the planning matrix (Table 1), a test was conducted. The results of the tests are presented in Table 2.

Table 2. The results of the tests

Test No		Planning matrix			Squares of variables			Interaction of factors			Result		
		x_1	x_2	x_3	x_{12}	x_{22}	x_{32}	x_1x_2	x_1x_3	x_2x_3	y_1	y_2	y_3
	1	+1	+1	0	+1	+1	0	+1	0	0	8	8	8
	2	+1	-1	0	+1	+1	0	-1	0	0	10	10	10
	3	-1	+1	0	+1	+1	0	-1	0	0	7	6	6
	4	-1	-1	0	+1	+1	0	+1	0	0	9	9	8
	5	+1	0	+1	+1	0	+1	0	+1	0	8	7	7
	6	+1	0	-1	+1	0	+1	0	-1	0	9	9	8
	7	-1	0	+1	+1	0	+1	0	-1	0	7	7	7
	8	-1	0	-1	+1	0	+1	0	+1	0	6	6	7
	9	0	+1	+1	0	+1	+1	0	0	+1	8	8	9
	10	0	+1	-1	0	+1	+1	0	0	-1	7	8	7
	11	0	-1	+1	0	+1	+1	0	0	-1	8	8	8
	12	0	-1	-1	0	+1	+1	0	0	+1	7	6	8
n_0	13	0	0	0	0	0	0	0	0	0	8	9	9
	14	0	0	0	0	0	0	0	0	0	9	8	10
	15	0	0	0	0	0	0	0	0	0	10	8	8

After conducting the tests, calculations of regression coefficients were performed, and the regression equation in the coded variables was obtained

$$\begin{aligned} Y = 8.667 - 1.025x_1 - 0.375x_1^2 + 1.025x_2 - 0.042x_2^2 + \\ +0.417x_3 - 0.958x_3^2 + 0.083x_1x_2 - 0.5x_1x_3 \end{aligned} \tag{1}$$

in this equation *Y* is the predicted value of the dependent variable for given values of x_1, x_2, x_3.

After obtaining the regression equation, the homogeneity of variances and reproducibility of the experiments were checked using the Cochrane criterion. The arithmetic mean value of *m* repeated measurements y_i, was calculated

$$y_{ave} = \begin{pmatrix} 8 \\ 10 \\ 6.333 \\ 8.667 \\ 7.333 \\ 8.667 \\ 7 \\ 6.333 \\ 8.333 \\ 7.333 \\ 8 \\ 7 \\ 8.333 \\ 9 \\ 8.667 \end{pmatrix} \tag{2}$$

Model coefficients are considered significant if their absolute values are greater than the confidence interval

$$|b_i| > \Delta b_i \tag{3}$$

Taking into account the value of expression (3), the dispersion of experimental reproducibility and the calculated value of the Cochrane criterion were calculated. The theoretical value of the Cochrane coefficient G_p = 0.222 was calculated according to the expression

$$G_p = \frac{D_{u\,\max}}{\sum_{u=1}^{N} D_u} \tag{4}$$

where D_u is the variance of each series of repeated experiments.

The tabular value of the Cochrane coefficient for 15 tests and three parallel experiments is G_p = 0.335. The calculated value of the Cochrane criterion is less than the tabular value. That is, the condition $G_p < G_{tabl}$ is met; therefore, it can be assumed that all calculated variances are recognized as homogeneous, and the experiments are considered reproducible. The significance of the regression coefficients was determined using the Student *t*-test.

The mean square errors were calculated according to the expression

$$\sigma_k = \sqrt{\frac{D_B}{N \cdot m}} \tag{5}$$

The obtained values of the mean square errors are given in Table 3.

The tabular value of the Student's *t*-test at $\alpha = 0.05$ is $t_{tabl} = 4.3$.

Since t_{11}, t_{22}, t_3, t_{33}, t_{12}, t_{13} and $t_{23} < t_{tabl}$, the coefficients b_{11}, b_{22}, b_3, b_{33}, b_{12}, b_{13} and b_{23} are insignificant. The quadratic coefficients b_{11}, b_{22}, and b_{33} are also insignificant, but they should not be removed from the model, because all quadratic coefficients are related not only to each other, but also to the free term.

The regression equation in coded quantities has the form

$$Y = 8.667 - 1.025x_1 - 0.375x_1^2 + 1.025x_2 - 0.042x_2^2 - 0.958x_3^2 \tag{6}$$

The regression equation in natural quantities has the form

$$Y = 9.155 - 4.25x_1 - 1.5x_1^2 + 0.017x_2 - 0.001x_2^2 - 0.958x_3^2 \tag{7}$$

After finding the regression equation, an assessment of adequacy was carried out. The adequacy variance was calculated using the expression

$$D_{adeq} = \frac{m}{N-L}\sum_{u=1}^{N}\left(y_u - y_u^p\right)^2 \tag{8}$$

Resulting value $D_{adeq} = 0.69$.

Calculated value of Fisher's exact test

$$F_p = \frac{0.69}{0.111} = 6.208 \tag{9}$$

The tabular value of this criterion F_{tabl} for degrees of freedom $f_1 = 2$, $f_2 = 9$ is 19.4. Accordingly, $F_p < F_{tabl}$, and therefore the obtained mathematical model is adequate for the experimental data. Using the obtained regression equations, the theoretical values of the response function were obtained

$$y_{ave} = \begin{pmatrix} 8.667 \\ 9.917 \\ 7.417 \\ 8.667 \\ 7.083 \\ 8.333 \\ 7.083 \\ 8.333 \\ 8.333 \\ 7.083 \\ 8.333 \\ 7.083 \\ 8.667 \\ 8.667 \\ 8.667 \end{pmatrix} \tag{10}$$

Table 3. Values of the mean square errors

Regression coefficient	b_0	b_1	b_{11}	b_2	b_{22}	b_3	b_{33}	b_{12}	b_{13}	b_{23}
	8.667	-1.025	-0.375	1.025	-0.042	0.417	-0.958	0.083	-0.5	0
Mean squared error	$\sigma_{\{b0\}}$	$\sigma_{\{b1\}}$	$\sigma_{\{b11\}}$	$\sigma_{\{b2\}}$	$\sigma_{\{b22\}}$	$\sigma_{\{b3\}}$	$\sigma_{\{b33\}}$	$\sigma_{\{b12\}}$	$\sigma_{\{b13\}}$	$\sigma_{\{b23\}}$
	0.365	0.224	0.329	0.224	0.329	0.224	0.329	0.316	0.316	0.316
Ratio *	23.73	4.58	1.14	4.58	0.13	1.86	2.91	0.26	1.58	0.00

* $t_k = \dfrac{|b_k|}{\sigma_{\{b_k\}}}$

3. Results

Experimental studies were conducted according to the Box-Behnken design with three variable factors: distance to the microphone (x_1), microphone sensitivity (x_2), and voice type (x_3). For each combination of factors, three parallel repetitions were performed, in each of which all ten possible voice commands were given. The number of correctly recognized commands was used as feedback. The average values of the results for each combination of factors are given in Table 2. The analysis showed that the largest number of correctly recognized commands (10) was observed at a distance of 1.0…0.5 m, high microphone sensitivity, and when using a male voice. The smallest values were recorded in cases of maximum distance and low microphone sensitivity.

Homogeneity of variances was checked using the Cochrane criterion (4). The calculated value of G_p was less than the tabulated value, which indicates homogeneity of variances and reproducibility of the experiments.

The significance of the regression coefficients was assessed using the Student's t-test (5), with the coefficients corresponding to the factors x_1 and x_2 being statistically significant, while the influence of the factor x_3 and interaction effects was insignificant.

Based on the experimental data, the regression equation was obtained in the coded variables (6) and the natural variables (7). The constructed model allows predicting the number of correctly recognized commands depending on the values of the studied factors.

The adequacy of the model was checked using the Fisher criterion (9). The calculated value was less than the tabulated value, which confirms the adequacy of the mathematical model to the experimental data.

Using the regression equation, response surfaces were constructed for fixed values of one of the factors (Figs. 5–7).

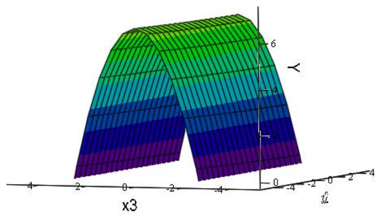

Fig. 5. The response surface at a constant factor x_1

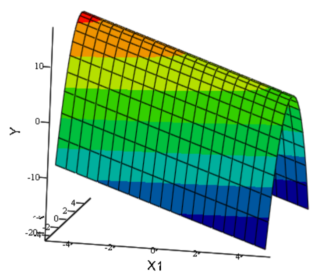

Fig. 6. The response surface at a constant factor x_2

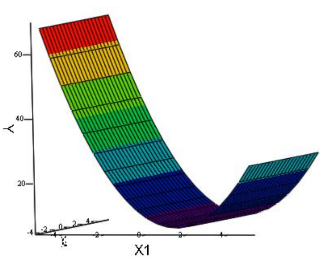

Fig. 7. The response surface at a constant factor x_3

Analysis of these surfaces showed that the optimal values of the factors within the studied range are:

- distance L = 0.5 m;
- sensitivity M_0 = -56 dB;
- voice type – male.

The results obtained confirm the effectiveness of the applied optimization method and allow us to recommend the specified parameters for configuring voice control systems for "smart home" elements.

4. Discussion

The proposed mathematical model has several limitations that should be considered when interpreting the results. First, the model was developed and validated within a predefined range of experimental parameters, including microphone sensitivity, distance, and background noise level. Extrapolation beyond these ranges may reduce prediction accuracy. Second, the experiments were conducted under controlled acoustic conditions; therefore, the model does not explicitly account for complex environmental effects such as reverberation, non-stationary noise, or multi-speaker interference. Third, the model operates at a system level and treats the cloud-based voice recognition service as a black-box, without incorporating internal algorithmic changes that may occur over time. Consequently, periodic recalibration may be required to maintain numerical accuracy under long-term deployment.

Analysis of the obtained results showed that the distance to the microphone (x_1) and the microphone sensitivity (x_2) are the most influential factors, which is confirmed by the values of the regression coefficients in model (6). The sign of the coefficients for these variables indicates that decreasing the distance and increasing the microphone sensitivity within the studied range have a positive effect on the number of correctly recognized commands. This is consistent with the results of [7, 9], where it is also shown that decreasing the distance reduces the influence of reverberation and noise, and increasing the sensitivity to a certain optimum improves the signal-to-noise ratio.

Comparison of the obtained values of the t-statistics with the tabular value t_{table} = 4.3 confirmed that only the coefficients at the factors x_1 and x_2 are significant. The adequacy of the model was checked using the Fisher criterion (9). The obtained value turned out to be less than the tabular value F_{table} = 19.4, which indicates the adequacy of the mathematical model to the experimental data. This means that the constructed quadratic model of the response surface describes the dependence of the number of correctly recognized commands on the studied factors within the specified limits.

The construction of response surfaces based on model (6) (Figs. 5–7) showed that at a distance of L = 0.5 m and a microphone sensitivity of M_0 = -56 dB, the maximum level of command recognition accuracy is observed. The male voice (x_3 = 1) demonstrated the best performance, which is probably due to the peculiarities of the training samples of the Google Assistant algorithms, which contain more data in the lower frequency range.

Comparison with the results of works [6, 20] shows that the achieved indicator (up to 10 out of 10 correct commands) is high in comparison with systems using multi-microphone arrays or special noise suppression algorithms. This indicates the effectiveness of the selected configuration and confirms the feasibility of using the Box-Behnken method for parameter optimization.

The studies were conducted under controlled conditions with low background noise (≈ 35 dB). As shown in [16, 19], in real conditions with increased noise or significant reverberation, the recognition accuracy can decrease by 10…20%. This determines the prospects for further research aimed at testing the system in more complex acoustic scenarios and implementing algorithms for automatic adaptation of microphone sensitivity.

5. Conclusions

In this paper, a voice control system for "smart home" elements was developed and experimentally investigated, implemented based on the WeMos D1 mini microcontroller module using the Google Assistant voice assistant and a mobile application created in the MIT App Inventor environment. The study was performed using the Box-Behnken methodology, which made it possible to determine the influence of the main technical and technological parameters on the accuracy of voice command recognition.

Three factors were investigated: distance to the microphone (x_1), microphone sensitivity (x_2), and voice type (x_3), each of which had three levels of variation. The number of correctly recognized commands out of ten possible was used as an indicator of response.

The results showed that the most significant influence on the efficiency of command recognition is the distance to the microphone and its sensitivity, while the voice type plays a secondary role.

Within the studied range, it was found that the maximum efficiency is achieved at a distance of L = 0.5 m, microphone sensitivity M_0 = -56 dB, and the use of a male voice. With these parameters, the system stably provides 100% of correctly recognized commands in laboratory conditions.

Regression equations in coded and natural variables allow predicting the efficiency of the system when changing the studied factors. Verification of the model using the Cochrane, Student, and Fisher criteria confirmed its statistical adequacy and reproducibility.

The proposed optimal settings can be used during the development and operation of similar IoT solutions to improve the convenience of control and increase the accuracy of voice command recognition without the implementation of complex and expensive technical solutions, such as multi-microphone arrays or additional computing modules.

The experiments were conducted under controlled acoustic conditions with a background noise level of approximately 35 dB(A). This allowed us to obtain maximum performance, but did not take into account the influence of variable factors of the real environment (noise from household appliances, reverberation, obstacles in the path of sound).

The next step should be to test the system in real-life conditions with different noise levels, variations in room acoustics, and changes in user positions. It is also advisable to implement algorithms for adaptive adjustment of microphone sensitivity and local automatic speech recognition systems, which will increase the autonomy and safety of the system.

Thus, the study not only confirmed the possibility of creating an effective voice control system based on available hardware and software, but also provided practical recommendations for its configuration to achieve maximum accuracy of command recognition. The proposed approach can be used as a basis for optimizing other IoT systems with voice interfaces.

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