

**Maximizing the load current of a ferromagnetic frequency doubler using a genetic algorithm**Oleh Kozak<sup>1</sup>, Volodymyr Samotyi<sup>2,3</sup><sup>1</sup> Ph.D. Student, department of "Computerized Automatics Systems", Lviv Polytechnic National University, Bandera str., 12, Lviv, 79013, e-mail: [oleh.v.kozak@lpnu.ua](mailto:oleh.v.kozak@lpnu.ua)<sup>2</sup> Doctor of Science, Professor, department of "Computerized Automatics Systems", Lviv Polytechnic National University, Bandera str., 12, Lviv, 79013, e-mail: [volodymyr.v.samotyi@lpnu.ua](mailto:volodymyr.v.samotyi@lpnu.ua)<sup>3</sup> Doctor of Science, Professor, department of "Automatics and Computer Science", Tadeusz Kosciuszko Krakow University of Technology, Warszawska str., 24, Krakow, 31155, e-mail: [vsamotiy@pk.edu.pl](mailto:vsamotiy@pk.edu.pl)

*This paper proposes the optimization of the load current of a ferromagnetic frequency doubler using a genetic algorithm (GA). The existing mathematical model is considered and its Python equivalent is developed. The developed model was compared with the original mathematical model. The existing Python libraries for GA are briefly reviewed. The pygad library is used for optimization and the given parameters are considered. The main optimization criterion is to maximize the value of the load current. Four rounds of optimizations were performed. The first three rounds of optimization required only a change in the input voltage within different limits, which does not require an actual change in the device. The fourth round of optimization, in turn, expanded the third round by additionally introducing changes in the parameters of the magnetic branches, which would require a physical change in the device. The use of GA made it possible to quickly optimize and adjust the optimizations based on the obtained values. The results of the optimizations showed a significant increase in the load current of the ferromagnetic frequency doubler compared to the baseline parameters before the optimization.*

**Keywords:** parametric optimization, genetic algorithm, steady-state, nonlinear mathematical models, frequency doubler, ferromagnetic frequency doubler, optimization algorithms.

**Introduction.** In the modern world, technologies are developing very rapidly, which is generally driven by innovation, competition, and demand. [1] One of the factors contributing to the rapid development is the exponential growth of computing power, which is well described in Moore's law, which predicts a doubling of the number of transistors in integrated circuits every 2 years. This trend clearly indicates the need to improve a device or system to maintain its place in the market.

Therefore, given the rapidly changing trends and rapid development, there is a need to keep abreast of current developments and issues, which in one way or another affects accuracy and efficiency. [2] One of the ways to get better results is to optimize. Optimization is an important process in engineering and scientific disciplines that ensures that systems and components operate at maximum efficiency and productivity. [3] Optimization applications are widely used in various fields, such as energy, [4] supply chain, [5] engineering, [6] chemical processes [7] and other areas.

In this article, we will consider the optimization of the load current of a ferromagnetic frequency doubler with a three-rod magnetic core using genetic algorithms. In control systems, there are two ways to perform optimization: the first is to experiment with a physical device, and the second is to reproduce these values by mathematical modelling. The first way requires the availability of a physical device and the introduction of changes to it. The second way, in turn, is an inexpensive means of research, which, of course, cannot completely replace the first, since experimental verification of the mathematical model is still required. However, the obvious advantage of a mathematical model is that it can be used in optimization problems by selecting different input data. Accordingly, a mathematical model has been developed in Python for optimization.

## 1. Problem statement

Optimization of a frequency doubler can be considered from different directions. For example, in [8], the optimization is mainly proposed based on the use of a round core in the transformer, instead of a rectangular or ellipsoidal core, which, according to the calculations presented, allows for lower winding losses and inductance losses compared to the latter two. In another article [9], the optimization is considered for three different circuits, substituting three predefined values into the simulation, and at the end, the optimization results are compared with each other. This approach is quite simple and optimization algorithms could show better results than a set of predefined data. In article [10], the optimization is focused on the process of developing a frequency doubler from scratch, proposing approaches to speed up this development. The proposed methods contain a window of opportunity, namely the extension of optimization through the use of Evolutionary Algorithms, such as Genetic Algorithms and others, which allows for a wider scope of optimization.

Frequency doubler circuits are not new, in this article, will be considered a ferromagnetic frequency doubler. Structurally, a ferromagnetic frequency doubler is a magnetic amplifier that contains an additional winding, and in it, in turn, the second harmonic is induced, while the first harmonic is absent, as in the control winding. Therefore, ferromagnetic frequency doublers, like magnetic amplifiers, can be designed with either split magnetic cores or three-rod circuits.

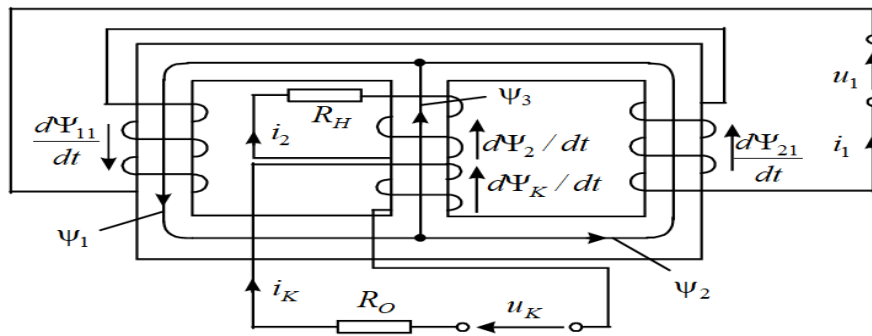


Fig. 1. Schematic diagram of a three-rod ferromagnetic frequency doubler.

Let's consider a three-rod ferromagnetic frequency doubler operating on an active load ( $R_H$ ) fig. 1. The flux coupling of the side cores  $\Psi_1, \Psi_2$  in the central core occurs, so the first harmonic is absent here.

## 2. Model of a ferromagnetic frequency doubler

The state equations of the magnetic circuits will be as follows: [11]

$$\left. \begin{aligned} i_1 + i_2 + i_c &= (\alpha'_1 + \alpha'_3)\psi_1 - \alpha'_3\psi_2 \\ 2i_1 &= \alpha'_1\psi_1 + \alpha'_2\psi_2 \end{aligned} \right\} \quad (1)$$

where  $i_1, i_2, i_c$  – currents of the supply, output and control windings;

$\psi_j (j = 1, 2)$  – operating flux coupling of the magnetic branches of the frequency doubler;

$\alpha'_j (j = 1, 2, 3)$  – inverse static inductances of the magnetic branches, determined according to (2).

The calculation formula for the inverse static inductances of the magnetic cores is determined by the main magnetisation curves

$$\alpha'_j (j = 1, 2, 3) = \varphi_j(\psi_j) / \psi_j = \alpha'_j(\psi_j) \quad (2)$$

where  $\varphi_j(\psi_j)$  – basic magnetisation curves, determined according to (3)

$$\varphi(\psi) = \begin{cases} a_1\psi, & |\psi| > \psi_{01}, \\ S_3(\psi), & \psi_{01} \leq |\psi| \leq \psi_{02}, \\ a_2\psi - a_0, & |\psi| > \psi_{02} \end{cases} \quad (3)$$

where  $S_3(\psi)$  – cubic spline;  $a_j (j = 0, 1, 2)$  – approximation coefficients.

The equations of electrical circuits are written in matrix form

$$\frac{d\Psi}{dt} = U - RI, \quad (4)$$

where  $\Psi = [\Psi_1, \Psi_2, \Psi_C]^T$  – matrix-column of full circuit flow-couplings, respectively, of the power supply, load and control circuits;

$U = [u_1, 0, u_C]^T$  – matrix-column of supply voltages of electrical circuits;

$I = [i_1, i_2, i_K]^T$  – matrix-column of winding currents;

$R = \text{diag}[r_{11} + r_{21}, r_2 + R_L, r_C + R_{Lim}]$  – diagonal matrix of active resistances of electrical circuits. Where  $r_{11}, r_{21}$  – resistances of the power supply windings;  $r_2, r_C$  – output winding and control resistances;  $R_L$  – load resistance;  $R_{Lim}$  – limiting resistance of the control circuit.

Solving (1) with respect to the currents, we obtain

$$i_1 = (\alpha'_1\psi_1 + \alpha'_2\psi_2) / 2, \quad \left. \begin{aligned} i_c &= \left( \alpha'_3 + \frac{\alpha'_1}{2} \right) \psi_1 - \left( \alpha'_3 + \frac{\alpha'_2}{2} \right) \psi_2 - i_2, \end{aligned} \right\} \quad (5)$$

The current equations are as follows

$$\left. \begin{aligned} i_1 &= \alpha_1(\Psi_1 - \psi_1 - \psi_2), \\ i_2 &= \alpha_2(\Psi_2 - \psi_1 + \psi_2), \\ i_C &= \alpha_C(\Psi_K - \psi_1 + \psi_2), \end{aligned} \right\} \quad (6)$$

where  $\alpha_1 = \alpha_{11}\alpha_{21}/(\alpha_{11}+\alpha_{21})$ ;  $\alpha_{11}, \alpha_{21}, \alpha_2, \alpha_C$  – inverse leakage inductances of the windings.

Let's substitute expressions (6) into the system of equations (1) and differentiate the result in time

$$\left. \begin{aligned} \alpha_1 \left( \frac{d\Psi_1}{dt} - \frac{d\psi_1}{dt} - \frac{d\psi_2}{dt} \right) + \alpha_2 \left( \frac{d\Psi_2}{dt} - \frac{d\psi_1}{dt} + \frac{d\psi_2}{dt} \right) \\ + \alpha_C \left( \frac{d\Psi_K}{dt} - \frac{d\psi_1}{dt} + \frac{d\psi_2}{dt} \right) = (\alpha_1'' + \alpha_3'') \frac{d\psi_1}{dt} - \alpha_3'' \frac{d\psi_2}{dt}, \\ 2\alpha_1 \left( \frac{d\Psi_1}{dt} - \frac{d\psi_1}{dt} - \frac{d\psi_2}{dt} \right) = \alpha_1'' \frac{d\psi_1}{dt} + \alpha_2'' \frac{d\psi_2}{dt}, \end{aligned} \right\} \quad (7)$$

де  $\alpha_j'' (j = 1, 2, 3)$  – inverse differential inductances of magnetic cores, which are calculated from the average magnetisation curves  $\alpha_j'' = \partial\varphi_j(\psi_j) / \partial\psi_j, j = 1, 2, 3$ .

Combining like terms, the system of equations (7) takes the form

$$\left. \begin{aligned} a_{11} \frac{d\psi_1}{dt} + a_{12} \frac{d\psi_2}{dt} = \alpha_1 \frac{d\Psi_1}{dt} + \alpha_2 \frac{d\Psi_2}{dt} + \alpha_C \frac{d\Psi_K}{dt}, \\ a_{21} \frac{d\psi_1}{dt} + a_{22} \frac{d\psi_2}{dt} = 2\alpha_1 \frac{d\Psi_1}{dt}, \end{aligned} \right\} \quad (8)$$

where  $a_{11} = \alpha_1'' + \alpha_3'' + \alpha_1 + \alpha_2 + \alpha_C$ ;  $a_{12} = \alpha_1 - \alpha_2 - \alpha_C - \alpha_3''$ ;  $a_{21} = \alpha_1'' + \alpha_1$ ;  $a_{22} = \alpha_2'' + 2\alpha_1$

The system of equations (8) can be written in matrix form

$$P \frac{d\psi}{dt} = \Lambda \frac{d\Psi}{dt} \quad (9)$$

where  $\psi = [\psi_1, \psi_2]^T$  – matrix-column of working flow couplings of cores;  $P, \Lambda$  – matrix coefficients

$$P = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}; \Lambda = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_C \\ 2\alpha_1 & 0 & 0 \end{bmatrix} \quad (10)$$

Having rotated the coefficient matrix P, equation (9) is written in the normal Cauchy form

$$\frac{d\psi}{dt} = P^{-1}\Lambda \frac{d\Psi}{dt} \quad (11)$$

where

$$P^{-1} = \frac{1}{\Delta} \begin{bmatrix} a_{22}, & -a_{12}, \\ -a_{21}, & a_{11} \end{bmatrix}; \Delta = a_{11}a_{22} - a_{12}a_{21}$$

Excluding, according to (4), the winding equations in expression (11), is obtained

$$\frac{d\psi}{dt} = D(U - RI), D = P^{-1}\Lambda \quad (12)$$

The current equation (6) is written in matrix form

$$I = \alpha(\Psi - H\psi), \quad (13)$$

where  $\alpha = \text{diag}[\alpha_1, \alpha_2, \alpha_C]$  – is the diagonal matrix of inverse leakage inductances of electrical circuits; H – structural matrix

$$H = \begin{bmatrix} 1, & 1, \\ 1, & -1, \\ 1, & -1 \end{bmatrix}$$

Differentiating by time (13)

$$\frac{dI}{dt} = \alpha \left( \frac{d\Psi}{dt} - H \frac{d\psi}{dt} \right), \quad (14)$$

Substituting (4), (12) into (14), is obtained

$$\frac{dI}{dt} = A(U - RI), A = \alpha(E - HD), \quad (15)$$

where  $E = \text{diag}[1, 1, 1]$  – diagonal matrix

Let us supplement the system of equations (12) with a differential equation with respect to the load current  $i_2$ , while  $i_1$  and  $i_C$  winding currents are calculated analytically according to expressions (5). The differential equation for the load current  $i_2$  is received from (15), is the second equation of this system of equations. To obtain it, it is enough to multiply (15) by the structural matrix  $H_1$

$$\frac{di_2}{dt} = A_2(U - RI), \quad A_2 = H_1A, \quad H_1 = [0, 1, 0]. \quad (16)$$

The system of equations (12), (16) is written in the single matrix equation form

$$\frac{dX}{dt} = B(\psi) \frac{dY}{dt}, \quad (17)$$

where  $X = [\psi_1, \psi_2, i_2]^T$  – state variable vector;  $B(\psi) = [D_1, D_2, A_2]^T$  – coefficients matrix, where  $D_1, D_2$  are the first and second rows of the matrix  $D$ ;  $\frac{dY}{dt} = U - RI$  – time function vector.

### 3. Development of a mathematical model of a ferromagnetic frequency doubler using Python

Python was chosen to develop this model of a ferromagnetic frequency doubler. Python is known for its simplicity and the number of available open source libraries, which plays an important role in development.

By numerically integrating equation (17) from the given initial conditions  $X(0)$ , is obtained a transient process, using the Runge-Kutta method. [12] It is advisable to calculate steady-state modes using a model of sensitivities to initial conditions. [13]

Figs. 2-4 show the calculated current curves for the analysis of the steady-state process of a ferromagnetic frequency doubler. The calculations were performed using the model of sensitivities to initial conditions. The supply voltage is given by equation  $u_1 = U_m \sin(\omega t)$  where  $U_m = 537.4$  V,  $\omega = 314.1593$  rad/s.

The calculations were performed using the following parameters:  $r_{11} = r_{21} = 1.5$  Ohm;  $R_0 = r_C = r_2 = 3$  Ohm;  $R_H = 17$  Ohm;  $\alpha_{11} = \alpha_{21} = 120$  H<sup>-1</sup>;  $\alpha_2 = 170$  H<sup>-1</sup>;  $\alpha_C = 100$  H<sup>-1</sup>;  $u_C = 100$  V.

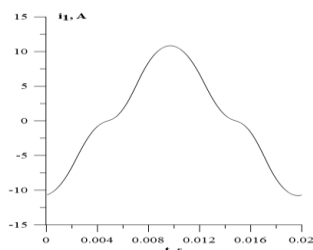


Fig. 2. Steady-state values of the supply winding current

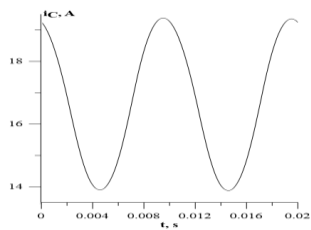


Fig. 3. Steady-state control winding current values

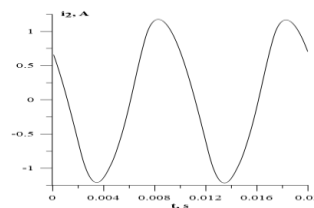


Fig. 4. Steady-state load current values

The magnetisation curves of the magnetic cores are taken to be the same and approximated by expression (3) with the choice of the calculation formula, where  $a_1 = 1.0 \text{ H}^{-1}$ ;  $a_2 = 50 \text{ H}^{-1}$ ;  $a_0 = 43 \text{ A}$ ;  $\psi_{01} = 0.5 \text{ Wb}$ ;  $\psi_{02} = 1.1 \text{ Wb}$ ;  $\varphi(\psi_{01}) = 0.5 \text{ A}$ ;  $\varphi(\psi_{02}) = 12 \text{ A}$ .

In Fig. 2 shows the results of calculating the steady-state current values of the power supply winding of the frequency doubler. Visually, it can be seen that its shape indicates an insignificant content of higher harmonics. Fig. 3. shows the steady-state values of the control current, which contains a constant component and the second harmonic. The load current (Fig. 4) has a clearly defined second harmonic. In all the figures, the abscissa axis shows time, namely one period of the supply voltage of 0.02 s. The developed Python model was compared with the original mathematical model, which allows us to proceed to the next stage - optimisation.

#### 4. Conducting optimization

Varieties of optimisation algorithms are used to solve optimisation problems, and in this article, Genetic Algorithms (GA) are used. As the name of the algorithm suggests, GA were inspired by nature, namely, they mimic the process of natural selection and genetics. These algorithms are very effective in solving problems with large nonlinear search spaces that are difficult to solve using conventional approaches. [14]

To perform the optimisation, it is necessary to have a GA implemented in Python. In general, there are two main approaches: the first is to recreate the algorithm based on its description, and the second is to use a ready-made library. The first approach requires much more time due to the error-prone nature and complexity of the algorithm implementation, while the second approach allows concentrating on solving the problem by using ready-made and time-tested functionality. As mentioned earlier, Python has many open-source libraries, so the next step is to find a library that implements GA. There are several libraries to choose from:

- genetic-algo – this library was released on 4 June 2023 and last updated on 31 July 2023. It's a fairly simple library, but it doesn't have a good documentation description.
- genetic-algorithm - this library was released on 7 November 2019 and last updated on 19 June 2021, and has a longer support period than the previous one. It contains short documentation as the functionality is also quite simple.
- pygad - this library appeared on 16 April 2020 and was last updated on 17 February 2024, was actively developed during this period and contained several major releases. The functionality of the library is extensive, including both GA and optimisation of machine learning algorithms. It also contains comprehensive documentation that covers all public methods and provides examples of use.

Of course, this list of libraries is not exhaustive, but these are some of the main ones that can be distinguished among the popular ones. The first two contain simplified functionality, which in theory could be enough, but they lack sufficient documentation, which is one of the important criteria for choosing a library. Another criterion is library support, which is also important because libraries are often released and not updated after that, but there is no such thing as perfect code and there may be problems in one place or another that the author could not avoid in advance. Therefore, taking into account all the above factors, the choice was made on the pygad library.

Optimisation can be considered in different ways, in this article we will focus on optimising the value of the load current  $i_2$ , namely by maximising the value. One way to achieve maximisation of the load current value is to change the control voltage  $u_C$  and the supply voltage  $u_1$  by changing  $U_m$ .

The fitness function is needed to assess the fitness of each individual. So before optimising, the fitness function needs to be recorded. In this case, the main criterion is to maximise the value of the load current  $i_2$ , so the fitness function will be quite simple, it's the maximum value of the load current in steady-state mode, for one period of the supply voltage, namely 0.02 s.

$$fitness = \max(i_2) \quad (18)$$

The following parameters were set for the GA: number of generations = 60, number of individuals per generation = 20, number of parents mating = 2, and selection of parents through a tournament. The next step is to set the search intervals for potential solutions of individuals. The following intervals are selected for individuals  $u_C \in [50, 220]$  and  $U_m \in [220, 600]$ , the search uses real numbers.

Individuals will provide solutions to the Python model developed in the previous section. To do this, the model needs to be integrated into the GA, in which case only 2 parameters are changed  $u_C$  and  $U_m$ , the rest of the parameters are the same as mentioned in the previous section. Therefore, the integration of the model into the GA is quite simple and requires only the replacement of input parameters, and the model itself does not require any changes.

After all the preparations and debugging of the programme, the optimisation was performed and the first results were obtained. The individual with the best fitness had the following results:  $u_C = 219.55$  V and  $U_m = 598.73$  V. Substituting the found values, the maximum obtained  $i_2 = 1.449$  A, it should be noted that with the values considered in the previous section, the maximum  $i_2 = 1.178$  A, so the optimisation shows a 23% increase from the initial values. Fig. 5 shows the results of the first optimisation.

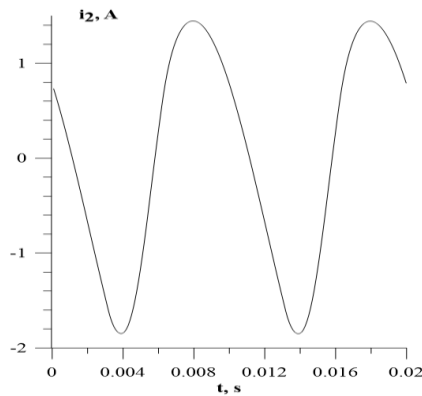


Fig. 5. Steady-state load current values after the first optimisation

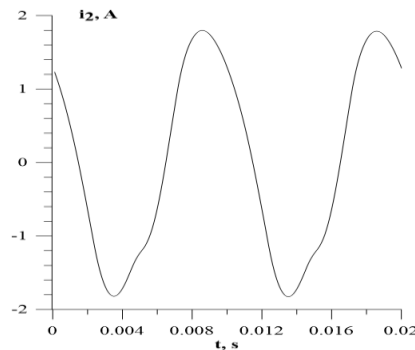


Fig. 6. Steady-state load current values after the second optimisation

After analysing the solution, can be observed that both values reached the upper limit of their search intervals. Therefore, for the second optimisation, the search intervals were changed  $U_m \in [220, 700]$  and for  $u_C$  the interval remained unchanged. After the second optimisation, the results were obtained, and the individual with the best fitness was selected:  $u_C = 51.64$  V and  $U_m = 699.95$  V. Fig. 6 shows the results of the second optimisation. For the second optimisation, the maximum  $i_2 = 1.797$  A, which is 24% more than in the first optimisation and 52.5% more than the initial values.

Again, the values can be seen to have reached the limit, this time  $u_K$  close to the lower limit of the interval and  $U_m$  to upper. So the search interval for was changed to  $U_m \in [220, 800]$ . After optimisation, an individual with the best fitness was obtained:  $u_C = 75.88$  V and  $U_m = 799.63$  V. Fig. 7 shows the results of the third optimisation. For the third

optimisation, the maximum value of  $i_2 = 2.087$  A, which shows an increase of 16% from the second optimisation and 77% from the initial values.

Similarly can be seen how the values have reached the limit, but this time only  $U_m$ . Of course, it is possible to keep increasing the upper limit for  $U_m$ , however, in practice, there will be very few areas where this can be applied. For example, over the past two years, there has been a trend towards the transition to 800 V battery architecture for electric vehicles. [15] Although the percentage of vehicles with this architecture is currently insignificant (a few percent), given its advantages and capabilities, it is expected that gradually in the coming years, the 800 V architecture will replace the 400 V architecture. [16] Taking into account these factors, it is reasonable to focus on the last selected voltage limits.

The previous optimisations included only changing the input voltage, which is quite convenient, since the actual device does not require any changes and is controlled only by the input parameters. However, in reality, there are situations when this is not enough. Often, a mathematical model is developed to simulate a certain change in the device or to try a new approach.

Changing the design parameters of the magnetic coils ultimately leads to a change in the inverse winding dissipation inductances, so it is these parameters that are operated on. For this optimisation, there will be more search intervals,  $u_c \in [50, 220]$  and  $U_m \in [220, 800]$  will remain unchanged. Additionally, new intervals will be introduced, namely  $\alpha_{11} = \alpha_{21} \in [70, 170]$ ,  $\alpha_2 \in [120, 220]$  and  $\alpha_c \in [50, 150]$ . After the fourth optimisation, the following values were obtained:  $u_c = 56.18$  V;  $U_m = 795.03$  V;  $\alpha_{11} = \alpha_{21} = 88.3$  H<sup>-1</sup>;  $\alpha_2 = 210.09$  H<sup>-1</sup> and  $\alpha_c = 50.62$  H<sup>-1</sup>. The results are shown in Fig. 8.

For the fourth optimisation, the maximum value of  $i_2 = 2.936$  A, compared to the third optimisation, the increase was 40% and compared to the value before optimisation 149%. If the results of the optimisations are compared visually, it can be seen that the first optimisation is most similar to a sinusoidal signal, while the last three have a slight distortion. It should be noted that after taking the characteristics on a real device, the actual values will have some deviations from the calculated ones, but this is expected.

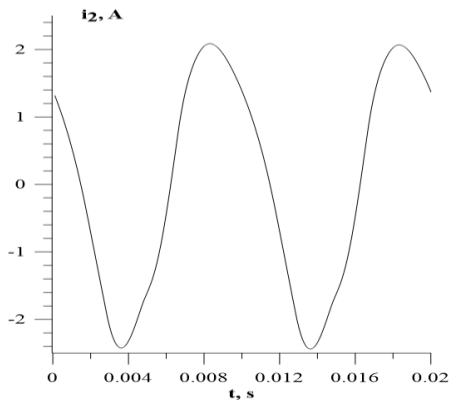


Fig. 7. Steady-state load current values after the third optimisation

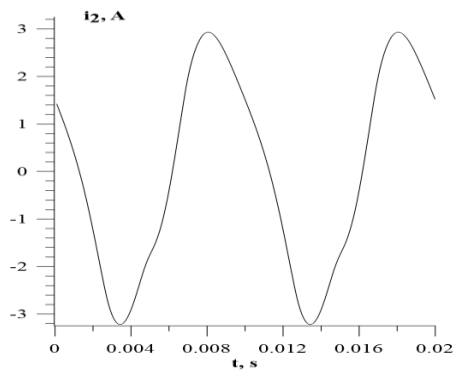


Fig. 8. Steady-state load current values after the fourth optimisation

**Conclusion.** This article discusses the optimisation of the load current of a ferromagnetic frequency doubler. In general, two approaches to optimisation are considered. The first approach required only the selection of the input voltage parameters, which in fact does not require any physical changes to the frequency doubler. The second approach includes the first one, and additionally introduces the search for the parameters of the inverse winding dissipation inductances, which in turn will require a constructive change of the frequency doubler.

The optimisation took place in four rounds. The first three rounds were performed according to the first approach. The maximum load current value obtained with this approach

showed an increase of 77% compared to the original values before optimisation. The fourth round was performed according to the second approach. The maximum load current value with this approach showed an increase of 149% compared to the original values and an increase of 40% compared to the first approach.

As can be seen from the results, optimisation is an important step and it allows for improved performance of a device or system. Mathematical models play an important role in this process, as they can be used to achieve significant results and try new approaches through simulation.

In this article, optimisation by maximisation has been discussed, but there may be problems that require finding an optimal value. For example, if the optimisation goal is to obtain a certain energy efficiency of a device, then the optimal value is not necessarily the maximum. Therefore, different problems will have different optimisation approaches.

Although the optimisation results are positive, further research should take into account the following nuances and ways to improve:

- Experimental data measurement on a real device, which would allow evaluating the obtained values and adjusting the model if necessary.

- Implementation of hybridised optimisation algorithms to improve the quality of found solutions and optimise the performance of the optimisation algorithm. [17]

- Use optimisation for other types of devices, as well as more complex systems (with dozens of variables) that are impractical and/or impossible to perform manually.

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## Максимізація струму навантаження феромагнітного подвоювача частоти із використанням генетичного алгоритму

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*В даній роботі розглянуто оптимізацію струму навантаження феромагнітного подвоювача частоти із використанням генетичного алгоритму (ГА). Розглянуто існуючу математичну модель та розроблено її відповідник мовою Python. Розроблену модель було звірено із оригінальною математичною моделлю. Коротко розглянуто існуючі Python бібліотеки для ГА. Для проведення оптимізації використано бібліотеку rugar і розглянуто задані параметри. Основним критерієм оптимізації є максимізація значення струму навантаження. Проведено чотири раунди оптимізації. Перші три раунди оптимізації потребували лише зміну вхідної напруги в різних межах, що не потребує фактичної зміни пристрою. Четвертий раунд оптимізації, в свою чергу, розширював третій раунд додатково вводячи зміну параметрів магнітних віток, що потребуватиме конструктивної зміни пристрою. Використання ГА дало можливість швидко проводити оптимізацію та коригування оптимізацій на основі отриманих значень. Результати оптимізацій показали значний приріст струму навантаження феромагнітного подвоювача частоти у порівнянні із базовими параметрами до проведення оптимізації.*

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