1. Abed BOUADI[1], 2. Houcine NAIM[2], 3. Mohamed DELLA KRACHAI[1], 4. Radouane FARES[2], 5. Guelta Bouchiba[2]

University of Science and Technology of Oran (USTO.MB), Algeria. (1), University Ahmed ZABANA,RELIZANE, Algeria. (2)
ORCID. 1. 00000-0003-2378-0292, 2. 000-0001-9980-8453, 4. 0000-0003-2702-374X

doi:10.15199/48.2022.04.15

Modeling and Simulation of a Novel Neural PLL controller for Circuit of Series Resonant Inverter in High Frequency Induction Heating

***Abstract**. This paper investigates of a novel PLL (Phase-Locked Loop) with neural control technology of induction magnetic heating system model at high power and high frequency, using neural controller to replace the traditional Low-Pass Filter (LPF). The PLL which control the inverter with SIT (Static Induction Transistor)-load-neural PLL assembly, the purpose of the PLL is to track the resonant frequency of the system. The continuation of the frequency by the conventional PLL has a certain delay and a large phase difference between the input signal of the PLL, and the output of the LPF. Therefore, to overcome this problem, we resorted to the networks of artificial neurons within the limits of what concerns us, the interest in them is justified by the characteristics they possess. To improve the control accuracy and response time. For more, the neural-controlled PLL controller for induction heating supply system have been analyzed and compared. A complete simulation model of the induction heating control system is obtained by Matlab/Simulink 6.5 software. The simulation results shows the effectiveness and superiority of this proposed neural PLL control system.*

Streszczenie. *W artykule zbadano nowy model PLL (Pętla Fazowa) z technologią neuronowego sterowania modelem indukcyjnego magnetycznego systemu grzewczego przy dużej mocy i wysokiej częstotliwości, przy użyciu sterownika neuronowego zastępującego tradycyjny filtr dolnoprzepustowy (LPF). PLL, które sterują falownikiem za pomocą zespołu SIT (Static Induction Transistor)-obciążenie-neural PLL, celem PLL jest śledzenie częstotliwości rezonansowej systemu. Kontynuacja częstotliwości przez konwencjonalny PLL ma pewne opóźnienie i dużą różnicę faz między sygnałem wejściowym PLL a wyjściem LPF. Dlatego, aby przezwyciężyć ten problem, sięgnęliśmy po sieci sztucznych neuronów w granicach tego, co nas dotyczy, zainteresowanie nimi jest uzasadnione posiadanymi przez nie cechami. Aby poprawić dokładność sterowania i czas reakcji. Co więcej, przeanalizowano i porównano sterowany neuronowo sterownik PLL do systemu zasilania nagrzewaniem indukcyjnym. Kompletny model symulacyjny układu sterowania nagrzewaniem indukcyjnym uzyskuje się za pomocą oprogramowania Matlab/Simulink 6.5. Wyniki symulacji pokazują skuteczność i wyższość proponowanego neuronowego systemu sterowania PLL.* (***Modelowanie i symulacja nowatorskiego sterownika neuronowego PLL dla obwodu szeregowego falownika rezonansowego w nagrzewaniu indukcyjnym wysokiej częstotliwości***)

Keywords: Neural control; Phase Locked Loop (PLL); Induction heating; resonant inverter.
Słowa kluczowe: PLL, sieć neuronowa, falownik rezonansowy

Introduction

Induction surface hardening is widely applied in transport, machine tool and metal industries, engaged in heat treatment of machining elements. The advantages that led to the widespread application of induction surface hardening include rapid heating, low scaling, less machining, fast cycle time, precise control of temperature, localised heating, no decarburization and no large-scale gain. Induction surface hardening is a heat treatment process used to increase the durability of machine tool elements subjected to high stresses. By durability is meant the improvement in the resistance to wear and greater torsion strength. Many types of steel are surface hardened with heat to increase toughness and resistance to wear. High quality alloy steel can be replaced by cheaper carbon steel which has been surfaced hardened by induction method. The induction method of hardening offers the possibility of confining the heat to the outer layer subjected to stresses without affecting the hardness of the core. A tough original core with hardened surface layer offers considerable mechanical and dynamic advantage[1–3].

With the development of power semiconductor devices, we were interested in modelling and simulation of an inverter with SIT (Static Induction Transistor) functioning at resonance and intended for the induction heating of high frequency ferromagnetic piece[1]. Induction heating power supply has more and more been used for the heating process. However, the changes of induction heating's temperature, melting furnace and other factors to cause load parameters and intrinsic resonant frequency will be changed. In order to make the inverter work always at a high power factor, which must increase the power supply output and frequency of inverter will be changed. This requires an automatic phase control circuit[4]. At present, induction heating power supply systems are generally use integrated phase locked loop (PLL)[5], such as CD4046 is used to track the phase of inverter output signal which may have a time varying frequency. Typical characteristics required for PLLs are quick pull-in, low jitter and a broad range of synchronization; many reports have been published on the improvement of these characteristics. However, with respect to PLLs for use at low frequencies, it is necessary to use large value capacitors and resistors in the loop filter to obtain the DC voltage needed for the VCO. When these are integrated in a chip, the area for these components is large and the problem of cost performance arises as the result[1,6,7].

In addition, induction-heating load is time-varying parameters, non-linear structure and so on. In the sophisticated and complex system of induction heating occasions difficult to achieve the desired effect of control.

In recent years, automatic control methods based on artificial intelligence approaches have emerged as an alternate paradigm to analytic control theory. Especially, neural control technology has been research and development. Neural control has superior control performance, particularly in handling nonlinearities and external disturbances with a strong coupling, time-varying parameters, and non-linear model for the complex system of control. When the system is non-linear systems, neural control can have a perfect control result. in this context, this paper will design a neural control technology applied to traditional PLL to control the induction heating power inverter circuit[1,6–9] .

System configuration

The block diagram of the PLL-controlled induction heating power supply system is illustrated in Figure 1, which have the inverter-loader-neural PLL unit. The load, modeled by and ,are in series with the capacitance .

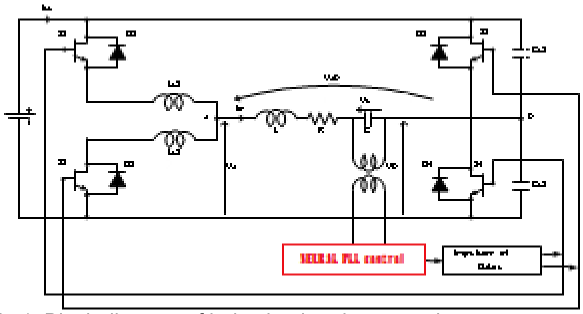

Fig.1. Block diagram of induction heating control system.

Neural Logic in the PLL

The operation Principle of Phase-Locked Loop

The insulation between the power circuits and the command was done by the insulation transformer connected at the boundaries of the capacitor. The period of the SIT attack signals followed the period of resonance via the Phase-Locked Loop (PLL)[10–12].

The Phase-locked loop, as shown in Figure. 2, is made up of a phase comparator (PC), from a low-pass filter (LPF) and from an voltage controlled oscillator (VCO) [9]. The phase comparator compares the phase of the input signal Vs(t) with that of the voltage controlled oscillator output V0(t) and generates the error voltage Vp(t) that is related to the phase difference between these signals. This error voltage is, then, filtered by the low-pass filter that removes the high frequency components to generate the control voltage Vf(t) for the voltage controlled oscillator. This control voltage, forces the voltage controlled oscillator frequency to vary in a direction that reduces the frequency to vary in a direction that reduces the frequency difference between the input signal and the voltage controlled oscillator output.

It will be then filtered by the low-pass filter (LPF) to eliminate the rows harmonics from higher and to produce the control signal Vc(t). This last signal forces the oscillator frequency to change to reduce the difference of phase and frequencies of output and input signals[8].

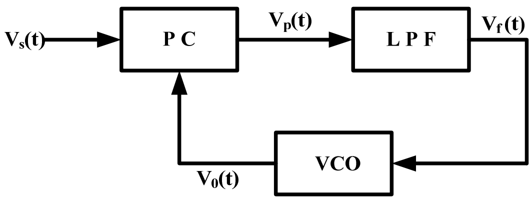

Fig. 2. Functional diagram of PLL

Simulation of the neural model

Neural control is based on a very powerful algorithm that is capable of controlling a wide range of difficult systems (non-minimal phase, significant dead time, non-linear, ..)[13]. The primary downside is that the system output can be predicted across a certain range of models. It is evident that the system output as shown in Figure3 may be predicted by a neural model.

We have built a simple network capable of learning the behavior of the LPF by the following PLL model:

Function

(1) $$F(u_1)\ :\ Y_1 = F(u_1) = \begin{cases} 1 \ \ si\ u_1 > 0 \\ 0 \ \ si\ u_1 < 0 \end{cases}$$

Function

(2) $$F(u_2)\ :\ Y_2 = F(u_2) = \begin{cases} 1 \ \ si\ u_2 > 0 \\ 0 \ \ si\ u_2 < 0 \end{cases}$$

(3) $XOR\ : Y = Y_1 \oplus Y_2$ With :

Function

(4) $$F(Y)\ \ Z = F(Y) = \begin{cases} V_c \ \ si\ Y \geq 0.5 \\ -V_c \ \ si\ Y < 0.5 \end{cases}$$

The Transfer function $\dfrac{nF(s)}{dF(s)}$:

(5)

$$Z_1 = \frac{nF(s)}{dF(s)} Z \ avec\ \frac{nF(s)}{dF(s)} = \frac{1}{\frac{1}{\omega c}s+1} = \frac{1}{s+1}$$

Y_1	0	1	1	0
Y_2	0	1	0	1
Y	0	1	1	1

With: Gain $K\omega$,

(6)

$$Z_2 = K\omega Z_1 = \frac{2\omega_0}{V_c} Z_1 \qquad ,$$

Frequency: $\omega = Z_3 = \omega_0 + Z_2$, The integrator and cos :

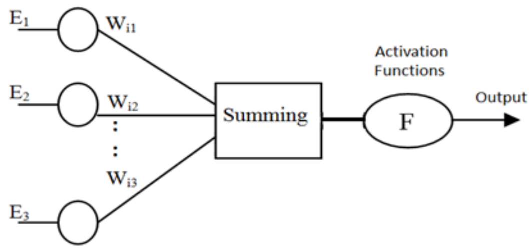

Fig. 3. The general diagram of an artificial neuron shapes.

(7) $$Z_4 = \frac{1}{s} Z_3$$

(8) $$Z_5 = \cos(Z_4)$$

Function :

(9) $$F(Z_5) = u_2 = \begin{cases} V_c \ \ si\ Z_5 \geq 0 \\ -V_c \ \ si\ Z_5 < 0 \end{cases}$$

Load model:

The summoner :

(10) $$Z_7 = -\dot{u}_1 + \dot{u}_1 - \dot{Z}_8 ,$$

The integrator:

(11) $$Z_8 = \frac{1}{s} Z_7 \text{, Gain : } \frac{1}{c_0} \ ,\ Z_9 = \frac{1}{c_0} Z_8$$

The variables $R(t)$ et $L(t)$:

(12) $$u_1 = \frac{1}{L(t)} u_1 \ ,\ \dot{u}_1 = \frac{1}{L(t)} u_0 \ ,\ \dot{Z}_8 = \frac{R(t)}{L(t)} Z_8$$

Voltage : $V_c = u_1$.

Identification is a procedure, which makes it possible to obtain a model of a process from a finite set of data made up of the inputs and outputs associated with this process.

The neural network used consists of four layers with two hidden layers, as shown in figure 4[14]. The inputs to the network are the voltage at the load terminal and the output voltage of the VCO (the two input voltages of the comparator); the output is the control law (filter output). The first hidden layer consists of ten neurons and the second of four neurons. The activation function of the first three layers is the sigmoid function and that of the output layer is the purelin function[15,16].

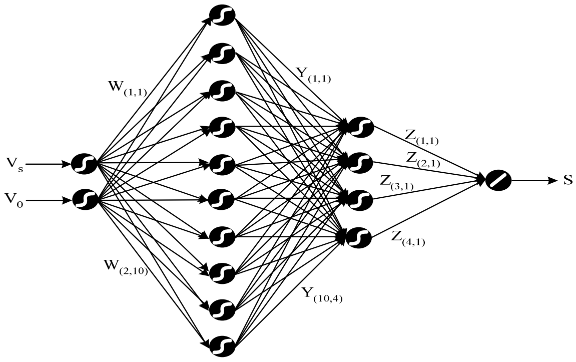

Fig. 4. Diagram of neurological networks.

In this phase, the network is trained to reproduce the control law as shown in Figure 5. The input and output of the filter are grouped together in a matrix which constitutes the prototype matrix. The Learning Parameters are:

- The admissible error e = 0.001,
- Maximum number of iterations = 100,000,
- Initialization: random,
- Activation function: hidden layer (logsig), output layer (purelin).

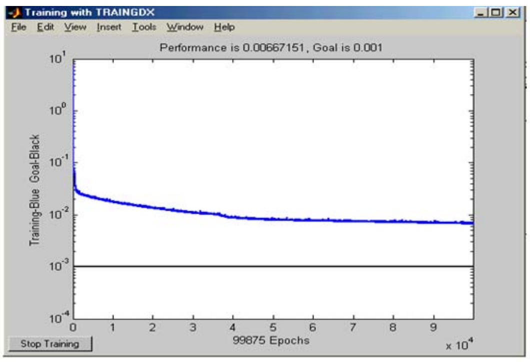

Fig. 5. Evolution of the error as a function of the number of iterations

The quadratic error has a nonlinear evolution characterized by a slope at the start, that is to say a high speed of convergence at the start, then it becomes slower and slower. We notice the decrease for the first 20,000 iterations is clearly greater than the iterations that follow it. This is explained by the fact that the corrections made to the weights and to the thresholds are proportional to the error made on each vector of the prototype presented; the latter decreases according to the number of iterations. We have introduced neural networks and we have seen their advantages in application in nonlinear systems which lies in:

- natural ability to approximate a nonlinear input / output function.
- adapts to variations in the modeled phenomenon.

The network we used is of the "feedforward" type with one input layer, two hidden layers and an output layer with supervised learning. From the theoretical study of induction heating and these principles started and the study of the PLL control of the inverter-load assembly in. The purpose of PLL is to track the resonant frequency of the system. The frequency tracking by the conventional PLL has a certain delay and a large phase difference between the input signal of the PLL and the output of the VCO (Voltage Controlled Oscillator[17]. In order to overcome this problem we have uses artificial neural networks within the limits of what concerns us, the interest in them is justified by the characteristics they possess[12,16,18,19].

System simulation

The model was studied and simulated by Matlab Simulink software version 6.5 Figure 6 and the parameters of the piece inductor assembly (,) vary. When heating the ferromagnetic part to keep the inverter operating at resonance, the operating frequency should follow the resonant frequency. The role of PLL control is to force the frequency of the system to continue the resonant frequency despite variations due to heating of the room. A model of the PLL was presented in order to simulate the inverter-load-PLL assembly[17].

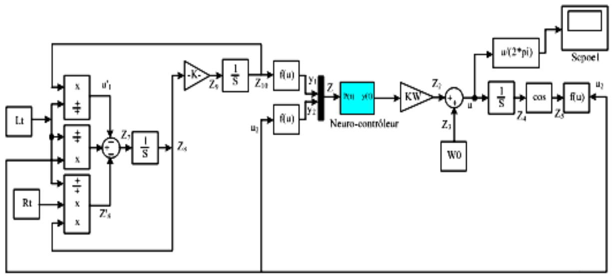

Fig. 6. Scheme of the system Inverter-Load-Neural PLL Matlab Simulation model.

Simulation Results and Interpretation

This phase consists of illustrating the results of simulations of our induction heating system before and after the application of the neural networks to the phase locked loop (PLL). We have for:

f_{PLL} : the frequency of the classic PLL.

f_{PLLN} : the frequency of neuronal PLL.

For initial values of $R(t)$, $L(t)$ and C_0 at resonance frequency of 400 kHz: $R_0 =$ 0.265 Ω , $L_0 = 2.533\ 10^{-5}\ H$ and $C_0 = 6.2501\text{e-}009\ F$

Figure 7 illustrates the variation of resonant frequency according to the temperature of heating. In the vicinity of the Curie point, inductance undergoes an abrupt change.

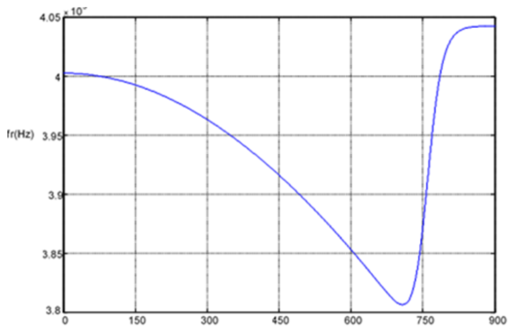

Fig. 7. Variation of the resonant frequency of the load (J_r)() according to the temperature of heating.

Figure 8. Show the variation of the resonant frequency (J_r) and those of PLL frequency (J_{PLL}) according to the heating temperature for the initial ones 520 kHz; (before the application of neural networks).

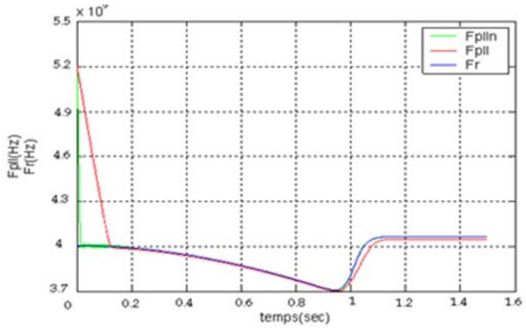

Fig. 8. Simulation results J_r, J_{PLL} and f_{PLLN} according to the heating time (Initial frequency of the J_{PLL} = 520 kHz).

We notice that the resonant frequency pursuit of the load was possible but with a delay and a large phase difference. The classic PLL has a somewhat long response time and a fairly large phase error. Figure 8 illustrate that the pursuit of the resonant frequency of the load is done correctly. Neural PLL has better performance: short response time and almost zero phase error. The problems encountered in the screen are resolved (after the application of neural networks).

Moreover, show very well the effect of neural networks on classical PLL, and that the desired performance was achieved after the application of neural networks.

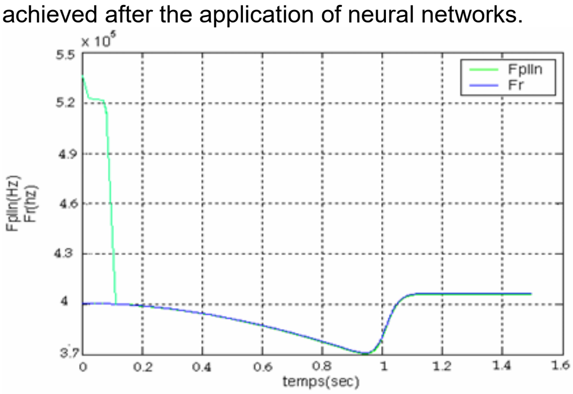

Fig. 9. Simulation results f_r, , J_{PLL} according to the heating time (Initial frequency of the f_{PLL} = 540 kHz).

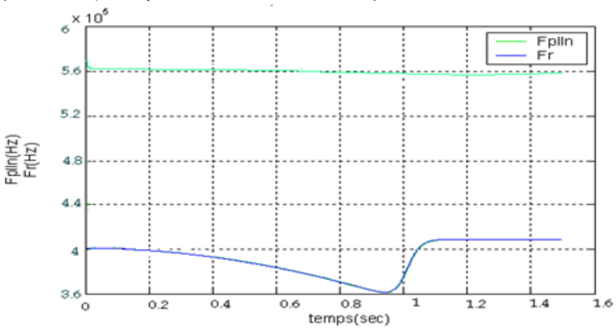

Fig. 10. Simulation results, f_r, , J_{PLLN} according to the heating time (Initial frequency of the f_{PLL} = 570 kHz).

Figures 9 and 10 show respectively the variations of the resonant frequency and those of the PLL frequency as a function of time for initial PLL frequencies of 540 kHz and 570 kHz.

At initial Fpll of 540 kHz, the neural PLL begins to unlock.

At initial Fpll of 570 KHz, the frequency of the neural PLL could not keep up with the resonant frequency.

It can be seen that neural PLL is more efficient than conventional PLL.

We notice that the tracking of the resonance frequency is done correctly for the initial ones of 550 kHz and 565 kHz.

The variation of the error was estimated at approximately 0.30 % at the hooking. When the initial value of the PLL frequency is 570 kHz, the tracking becomes impossible (beach of hooking exceeded).

Conclusion

The results show that the effect of the variation of the electrical and magnetic parameters of the metal is very significant. Its presentation in terms of frequency-heating time profile enabled to perform a load-frequency adaptation control in order to maximize the power transmitted to the load. In addition, it helped to ensure the soft commutation and to keep the system at maximum efficiency. In order to validate the proposed approach a numerical simulation under the Matlab / Simulink 6.5 is carried out. Furthermore, the control technique of high-frequency bridge resonant type inverters for induction heating applications (5 kW, 450kHz) employing SITs (Static Induction Transistor) as the switching devises. It was found that by a proper choice of the compensating capacitors, the inverter could run at unity power factor with maximum current gain and maximum efficiency.

The results obtained prove the reliability of the application of PLL neural networks for resonant frequency tracking. Tracking the resonant frequency has worked well when applying neural networks so the PLL frequency (Fplln) closely follows the resonant frequency (Fr).

By comparing neuronal PLL and conventional (PLL), we notice that the neural PLL offers better performances than that of the conventional PLL. "Off-line" learning has been done. "On-line" learning is desired to properly test the performance of the neural PLL. Tests carried out on induction heating systems give more refined simulation results than those obtained by conventional PLL.

***Authors**: dr BOUADI Abed Research Professor in Laboratory for Analysis and Applications of Radiation (LAAR), Physics Faculty, University of Science and Technology of Oran (USTO.MB), Algeria. E-mail: abed.bouadi@univ-usto.dz; dr Naim Houcine Phd Physic in Laboratory for Analysis and Applications of Radiation (LAAR), Department of Physics, University Ahmed ZABANA,RELIZANE, Algeria E-mail: houcine.naim@univ-relizane.dz; dr M. Della Krachai3, Department of Electronics, University of Science and Technologies – Mohamed Boudiaf, Algeria. E-mail: Mohamed.dellakrachai@univ-usto.dz; dr FARES Redouane–Phd in Physic Laboratory Industrial Engineering and Sustainable Development, University Ahmed ZABANA,RELIZANE, Algeria. E-mail : redouane.fares@univ-relizane.dz; dr Bouchiba Guelta phd in Computer Science University of Science and Technology of Oran (USTO-MB),Algeria. E-mail: bouchiba.guelta@univ-usto.dz*

REFERENCES

[1] Bouadi A, Naim H, Lounis M, Modeling and Simulation of PLL-Controlled Circuit of Series Resonant Inverter in High Frequency Induction Heating, Int. Rev. Autom. Control. 8 (2015).
[2] O. Lucia, P. Maussion, E.J. Dede, J.M. Burdio, Induction heating technology and its applications: Past developments, current technology, and future challenges, IEEE Trans. Ind. Electron. 61 (2014) 2509–2520. https://doi.org/10.1109/TIE.2013.2281162.
[3] H. Fujita, N. Uchida, K. Ozaki, A New Zone-Control Induction Heating System Using Multiple Inverter Units Applicable Under Mutual Magnetic Coupling Conditions, 26 (2011) 2009–2017.
[4] D.P. Ć, A.Ž. Ć, D.B. Ć, D.P. Ć, Recursive PLL of the First Order, (2013) 50–53.
[5] S. Cygan, M. Łukowicz, Analysis of the synchrophasor estimation problem, Prz. Elektrotechniczny. 94 (2018) 84–88. https://doi.org/10.15199/48.2018.11.20.
[6] Y. Wang, J. Song, F. Cao, Study on a novel fuzzy PLL and its

application, 2009 Int. Work. Intell. Syst. Appl. ISA 2009. (2009) 1–3. https://doi.org/10.1109/IWISA.2009.5073130.
[7] H. Calleja, R. Ordoiiez, Improved induction-heating inverter with power factor correction, (1999).
[8] B. Chatterjee, S. Sarkar, Introduction of Fuzzy Logic Controller in a Modified Phase-Locked Frequency Divider Leading to an Exceptional Noise Rejection, Springer Singapore, 2021. https://doi.org/10.1007/978-981-15-7834-2_84.
[9] V. V. Matrosov, M.A. Mishchenko, V.D. Shalfeev, Neuron-like dynamics of a phase-locked loop, Eur. Phys. J. Spec. Top. 222 (2013) 2399–2405. https://doi.org/10.1140/epjst/e2013-02024-9.
[10] L. Tan, P. Fu, Y. Wu, J. Lu, X. Shen, J. Li, Y. Tian, A novel phase-locked loop applied on frequency fluctuation of EAST power supply, Energy Reports. 6 (2020) 452–461. https://doi.org/10.1016/j.egyr.2020.11.214.
[11] J. Marcos Lobo da Fonseca, F. Kleber de Araújo Lima, F. Lessa Tofoli, C. Gustavo Castelo Branco, Three-phase phase-locked loop algorithms for the detection of positive-sequence and negative-sequence components, Int. J. Electr. Power Energy Syst. 126 (2021) 106570. https://doi.org/10.1016/j.ijepes.2020.106570.
[12] N. Ferhatović, S. Lale, J. Kevrić, S. Lubura, Implementation of Single-Phase Phase-Locked Loop with DC Offset and Noise Rejection Using Fuzzy Logic Controller, (2021) 407–421. https://doi.org/10.1007/978-3-030-54765-3_28.
[13] Y. Xie, Y. Zhou, A novel method on PLL control, Lect. Notes Electr. Eng. 97 LNEE (2011) 335–342. https://doi.org/10.1007/978-3-642-21697-8_42.
[14] T.H. Dos Santos, A. Goedtel, S.A.O. Da Silva, M. Suetake, Scalar control of an induction motor using a neural sensorless technique, Electr. Power Syst. Res. 108 (2014) 322–330. https://doi.org/10.1016/j.epsr.2013.11.020.
[15] B. Meziane, H. Zeroug, Comprehensive Power Control Performance Investigations of Resonant Inverter for Induction Metal Surface Hardening, IEEE Trans. Ind. Electron. 63 (2016) 6086–6096. https://doi.org/10.1109/TIE.2016.2581145.
[16] A. V. Milov, V.S. Tynchenko, A. V. Murygin, Neural network modeling to control process of induction soldering, 2019 Int. Conf. Ind. Eng. Appl. Manuf. ICIEAM 2019. (2019) 1–5. https://doi.org/10.1109/ICIEAM.2019.8743031.
[17] P. Vishnuram, S. Ramasamy, P. Suresh, A. Sureshkumar, Phase-Locked Loop-Based Asymmetric Voltage Cancellation for the Power Control in Dual Half-Bridge Series Resonant Inverter Sharing Common Capacitor for Induction Heating Applications, J. Control. Autom. Electr. Syst. 30 (2019) 1094–1106. https://doi.org/10.1007/s40313-019-00515-5.
[18] A. Rauh, E. Auer, Modeling, Design, and Simulation of Systems with Uncertainties, Math. Eng. 3 (2011). https://doi.org/10.1007/978-3-642-15956-5.
[19] Berner Rico, Patterns of synchrony in complex networks of adaptively coupled oscillators, 2020. https://depositonce.tu-berlin.de/handle/11303/11721.