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Perspective

Neural Network Applications in Electrical Drives—Trends in Control, Estimation, Diagnostics, and Construction

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Abstract: Currently, applications of the algorithms based on artificial intelligence (AI) principles can be observed in various fields. This can be also noticed in the wide area of electrical drives. Consideration has been limited to neural networks; however, the tasks for the models can be defined as follows: control, state variable estimation, and diagnostics. In the subsequent sections of this paper, electrical machines, as well as power electronic devices, are assumed as the main objects. This paper describes the basics, issues, and possibilities related to the used tools and explains the growing popularity of neural network applications in automatic systems with electrical drives. The paper begins with the overall considerations; following that, the content proceeds with the details, and two specific examples are shown. The first example deals with a neural network-based speed controller tested in a structure with a synchronous reluctance motor. Then, the implementation of recurrent neural networks as state variable estimators is analyzed. The achieved results present a precise estimation of the load speed and the shaft torque signals from a two-mass system. All descriptions in the article are considered in the context of the trends and perspectives in modern algorithm applications for electrical drives.

Keywords: adaptive neural control; state variables estimation; diagnostics; neural data processing; neural networks; electrical drives

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1. Preliminaries and Short Description of Methodology

Modern electrical drives can achieve improved ratios related to precision and reliability due to new materials and high-quality components [1–3]. The second area of development involves the algorithms applied to the objects. The trends observed in the papers published in the journals and proceedings of conferences are focused on artificial intelligence [4–6]. A group of the applications is focused on neural networks [7–11].

The main feature, which is the source of its use in most applications, is a flexible structure with adaptable parameters, i.e., weights. The optimization performed under training calculations leads to changes in the network parameters that increase the precision of the training data representation. Thus, the neural network output y_{nnl} can calculate a value of complex functions Φ based on the values of the weights $\mathbf{w}$, biases $\mathbf{b}$, and input signals $\mathbf{x}$:

$$y_{nn} = \Phi(\mathbf{w}, \mathbf{b}, \mathbf{x}), \tag{1}$$

$$y_{nnl} = \phi_o\left(\sum_{h=1}^{N_h} v_{lh}\phi_i\left(\sum_{i=1}^{N_i} w_{hi}x_i + w_{h0}\right) + v_{l0}\right), \tag{2}$$

where N_h is the number of nodes in the hidden layer, N_i is the number of nodes in the input layer, ϕ_o is the activation function of the hidden layer, ϕ_i is the activation function of the input layer, o is the number of outputs ($l = 1, 2, 3, \ldots, o$), v_{lh} represents the weights of the output layer, w_{hi} represents the weights of the input layer, v_{l0} represents the bias values of the output layer, and w_{h0} represents the bias values of the input layer.

In engineering applications, the model is capable of data representation (often in contrast to algorithmic methods), even if the signals in the processing are incomplete, nonlinear, uncertain, or disturbed (e.g., during measurement). Gradient methods are the most efficient for this purpose (3) and (4). Updates of network values are searched according to the assumption of finding the minimum value of the proposed objective function (5) and (6). Additionally, second-order training methods, based on cost function analysis, are used. This can lead to better results for more complex tasks due to the deeper evaluation of the state of the network, as shown in [12]. More complicated computation of the basic version of the known algorithms (e.g., Levenberg–Marquardt) provides a faster reduction in the cost function during the training process. The effectiveness of the mentioned algorithm in the training of neural networks has resulted in numerous modifications and improvements. Parallel data processing [13] and computational simplifications [14] have also been proposed.

$$v_{lh} = v_{lh} - \alpha \frac{\partial E}{v_{lh}} \tag{3}$$

$$w_{hi} = w_{hi} - \alpha \frac{\partial E}{w_{hi}} \tag{4}$$

$$e_l = \varrho_l - y_{nnl} \tag{5}$$

$$E = \frac{1}{2} e^T e = \frac{1}{2} \sum_{l=1}^{o} e_l^2 \tag{6}$$

$$\frac{\partial E}{\partial v_{lh}} = \frac{\partial E}{\partial z_l} \frac{\partial z_l}{\partial v_{lh}} \tag{7}$$

$$\frac{\partial E}{\partial w_{hi}} = \frac{\partial E}{\partial z_h} \frac{\partial z_h}{\partial w_{hi}} \tag{8}$$

The first ideas, propositions, and some contributions to mathematical representation were presented in the middle of the last century [15]. One of the most known publications presenting the concept of a neural model was presented by Warren S. McCulloch and Walter Pitts [16] and the basics of adaptation and neural network learning were presented by Donald O. Hebb [17]. Small adaptable units (ADAptive LInear NEuron) were combined in MADALINE networks and a simple algorithm, least mean square, was proposed for weight update by Bernard Widrow and Marcian E. Hoff [18]. The above-mentioned works have started new scientific disciplines derived from mathematics, computer science, and cognitive sciences. However, two factors can be consider to be the 'game changers' that have moved neural networks from theory to the implementation. One factor is related to calculating the partial derivative of the cost function according to the weights: the information used in the training process in Equations (3) and (4). The technique of backpropagation has allowed for the collection of an error value at each point of the network [19]. The initial phase assumes the propagation of the input data across the model; then, the output error is returned to the network input (using derivatives from the network and the derivatives of the cost function). The mathematical notation of the whole operation is often described using the chain rule (Equations (7) and (8)). The two-stage process can be treated as a disadvantage (output values of the corresponding layers are applied in formulas z_l and z_h). Therefore, other solutions for the gradient optimization of the weights have been proposed [20]. However, for software and hardware implementations, the backpropagation of error in a neural network is a definite advantage (over other methods for derivative determination). A separate issue contributing to the increase in neural network industry applications concerns programmable devices. In recent years, not only an increase in available systems has been observed, but also a significant reduction in price and an increase in computing capabilities (Figure 1). There are special processors dedicated exclusively to algorithms that perform neural calculations [21]. Moreover, power consumption is also considered [22].

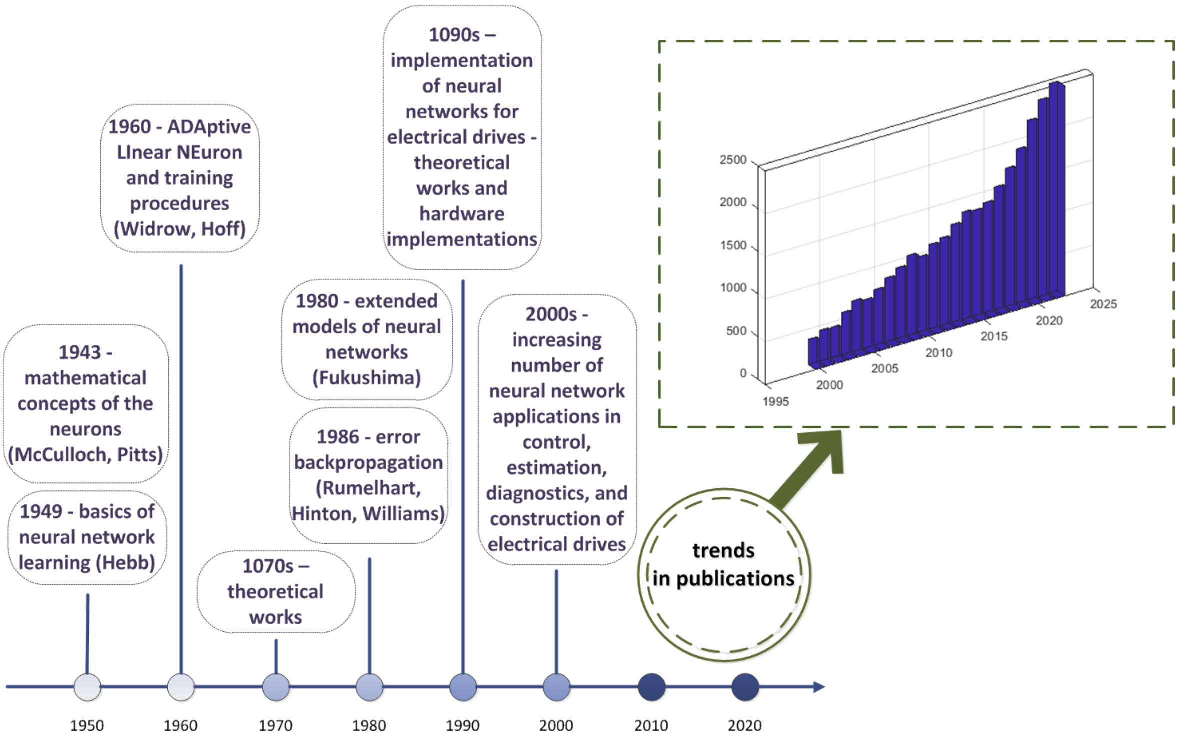

Figure 1. Timeline and milestones in neural network development, implementations in the field of electrical drives, and expansion of the number of articles (according to the Scopus database) in recent years (2000–2022).

From an application point of view, the mode of the weight update during optimization is a key point for determining the role of the neural network in the algorithm cooperating with the electrical drive (Figure 2). Firstly, calculations can be performed in an *offline regime*. In this context, this means that the collection of prior data for representation of the task is performed (e.g., detection of faults based on pre-generated symptoms). Then, the samples are used in network optimization. Following these steps, the neural model can be used in an electrical drive. The above assumption minimizes the cost function for improved data recovery. The model can be a signal generator (estimator in control structure), classifier for the input values (detection of faults), predictor of events (damages to machines), etc. The second approach—*online training*—includes a net in the control structure. The update of weights is realized in parallel with each step of the whole algorithm. The objective function is minimized again. However, an appropriate definition leads to a reduction in the control error. The difference between the forcing signal and the output is reduced, yet the network output is not considered, only the output of the controlled object. In this way, a control signal is generated at the network output, which will cause the motor speed to follow the input trajectory (reference speed).

The output values of a neural model can be calculated from the input data used in training. However, the important attribute is known as generalization. The net can achieve correct values for a given task, even if the input sample was not included in the training set. In real-life applications, if collecting a complete set representing a process or object is often impossible, this is a very useful functionality. Improvements in the mentioned properties of neural networks can be obtained through a variety of methods that are described in scientific publications. This applies not only to the optimization of the network coefficients for a given task; the topology of the model is also often modified. A summary of the most popular techniques is presented in Figure 3.

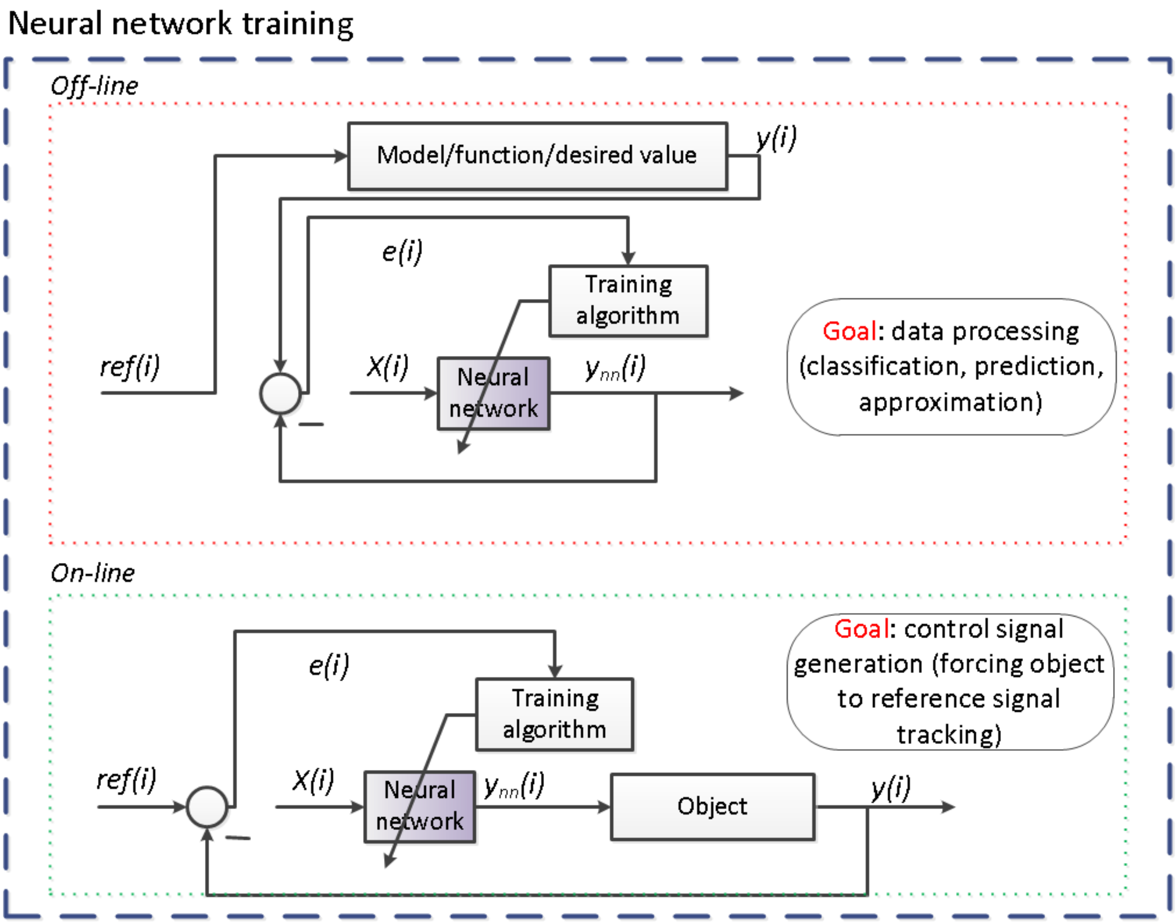

Figure 2. Optimization of neural networks for engineering applications.

It is commonly known that the number of training epochs defined for the calculations significantly influences the fitting of data using the neural model [23]. Increasing the number of iterations results in an improved agreement with the training data. The problem, in this case, is related to the reconstruction of disturbances and the lower accuracy after entering data outside the training set. In an opposite solution, the network cannot be sufficiently optimized to obtain the trends of the samples. Thus, analyzing the validation error during the training of the neural network can be an appropriate action. One non-classical approach to training neural networks is based on the application of meta-heuristic algorithms [24,25]. The methods mentioned are often based on swarm observations, where a population is a group of potential solutions and while processing is iteratively repeated, modifications are introduced according to the minimization of the objective function. This approach differs from a typical training algorithm based on the gradient of the cost function because it does not need calculations of the derivatives. The most popular methods of this type are genetic algorithms and particle swarm optimization [25–27]. As recently shown in [25], such solutions increase the convergence and recognition efficiency of neural networks. Both features are crucial in the field of electrical drives for improving dynamic properties during parameter changes and ensure accurate state and fault detection. The basic task of the mentioned algorithms is the selection of network weighting coefficients. However, there are also applications in which the structure of the model [28–30] or the initial values of the network parameters are optimized [31]. Regularization is also widely used for neural networks to overcome overfitting [32–34]. The method assumes an extension of the objective function by introducing additional penalty terms. It often leads to a different decomposition of weights. The dominant values are eliminated, and the distribution is even for all coefficients; therefore, irrelevant nodes or connections do not occur. The issues related to the design of neural models in the context of improving generalization properties concern optimization of the structure. This is one of the most effective approaches, which additionally determines the computational complexity (especially important during implementation). There are two groups of training procedures: growth methods [35–37] and pruning methods. Both of them are combined with common (gradient-based) training methods. However, the topology of the network is also modified. Subsequent neurons or connections are inserted into the net (growth methods), reducing the model complexity in comparison to the initial model. For the second solution, calculation of the 'saliency parameter' is of paramount importance [38–40]. Based on this information, the network connections are deleted (weights made equal to zero).

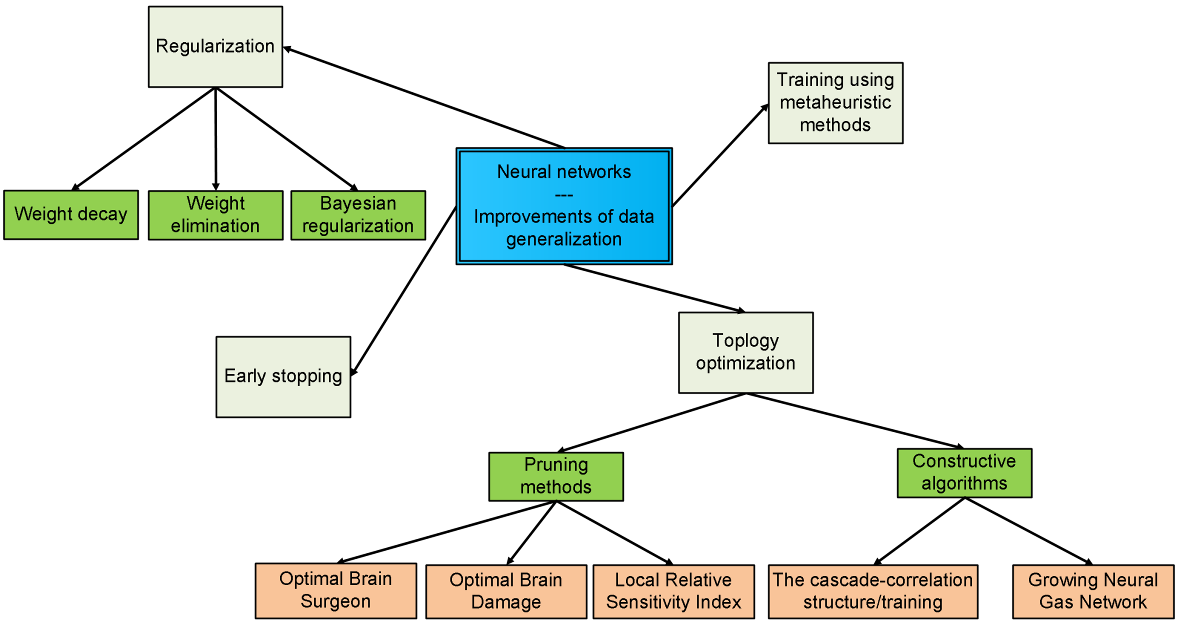

Figure 3. Training of neural networks: enhancing generalization properties.

In the theory of neural networks, the simplest models (ADALINE, MLP, RBF, etc.) have evolved into much more complex ones. Firstly, for better processing of the time-series data, recurrent neural networks were introduced [41,42]. Then, subsequent elements (e.g., convolutional layers, pooling layers, etc.) and significantly larger structures led to a subgroup of machine learning: deep learning. Deep neural networks are efficient tools in engineering applications related to processing data with a large number of samples or for data that represent more complex relationships [43,44]. However, a significant drawback is related to the complexity of this structure, which negatively impacts the training process and the subsequent implementations in programmable devices. Thus, the commonly known topology modification was proposed in articles [45–47]. Effective reduction in the neural network structure can be achieved using approaches that utilize graph reduction tasks. Recently, a concept based on the learning automaton has been proposed to optimize the cloud of sensors [48]. In this solution, a scheduling algorithm supported by machine learning is utilized to fulfill requirements important in the field of self-powered networks, such as covering the environment and balancing (limiting) energy consumption. Although the described approach has been only evaluated in simulated IoT environments, it is a promising concept for applications that optimize neural network structure. In addition to the reduction in required computational power, the precision of results can also be increased by using novel neural network topologies [49]. Thus, it is an expected research trend in the coming years.

The aim of the manuscript is to present the tools (neural networks) in the context of application properties and the observed implementations in electrical drives. The models proposed in theory can lead to the achievement of specific features, such as data generalization and rendering of non-linear dependencies. This determines the wide range of applications in the processing of signals in systems based on electrical machines. The main possibilities are described in the article and supported by actual references. Moreover, original examples are presented and analyzed. However, the most important purpose of this publication is to present trends in the literature related to electrical drives and to try to describe some expected directions for future research. The main contributions of this paper are listed as follows:

- Definition of the advantages and disadvantages of solutions based on neural networks used in electrical drives;
- Description of the current issues regarding the implementations of the neural models in control, state variable estimation, and diagnostics;
- As exemplary results that prove selected possibilities, the neural estimators (of load speed and shaft torque) used in a drive with an elastic shaft and adaptive controllers of reluctance motor are considered;
- Analysis of the directions in the development of neural network applications in the field of electric drive.

The content of this article is organized as follows. The first section presents a review of the algorithms, analyzing the properties of the neural networks along with their improvements and potential applications (Figure 4). It should be noted that in this field, topics related to the construction and design of machines constitute a separate important group (not analyzed in the manuscript). Then, in the subsequent sections, the neural networks are considered as controllers in automatic systems or state observers. The latter part of this paper (Section 2.3) concerns neural network applications in developing, modeling, optimizing, and controlling power converters, which are an important part of modern electrical drives. The next part of the article presents the tools used in diagnostics (standalone or hybrid with classical solutions known from control theory). The work is finalized with conclusions—highlights from each of the perspectives.

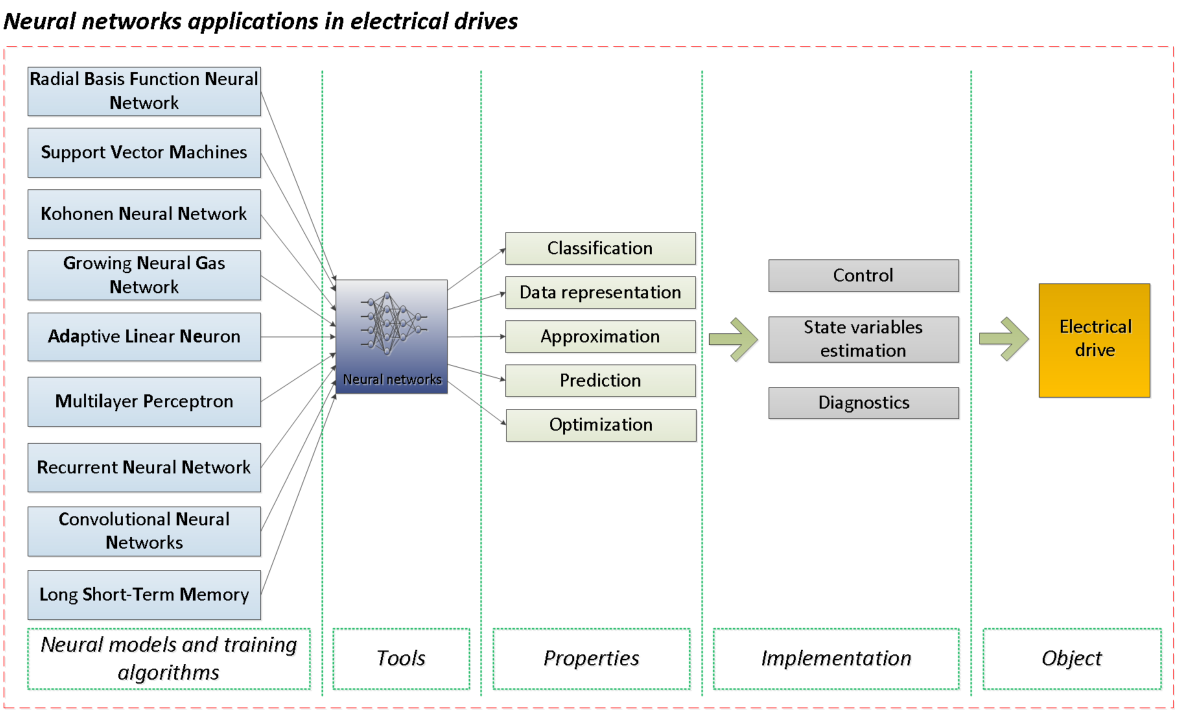

Figure 4. Neural networks—from theory to applications in electrical drives.

2. Implementation of Neural Models in Electrical Drives

2.1. Neural Controllers

The typical speed control structure applied in electrical machines can be divided into two parts: the internal, which is used for dynamic control of electromagnetic torque, and the external, with the loop related to speed. This scheme, in general, is suitable for different types of machines. Conventional PI (proportional–integral) or PID (proportional–integral–derivative) controllers are commonly applied in industry. This is due to the simple algorithm that facilitates implementation and the well-known tuning methods. However, currently, the trend seems to be changing. Advanced control methods are being more readily introduced in the industry. This comes from access to new tools: programmable devices and libraries providing high-level code implementation. In this way, it is possible to meet the high precision requirements for industrial equipment operation. In addition, improved properties are obtained for objects where parameter mismatch is observed. The issue may be related to the difficult identification of objects or changes in acting conditions (change of parameters due to motor heating and the fluctuation of the moments of inertia of actuators) [50–53].

The application of a neural network is one solution to the issue analyzed above. It can be used as an approximator of non-constant coefficients or as a multi-parameter adaptive model. In the first case, the neural network can be successfully applied to approximate nonlinear and non-constant coefficients of complex controllers. A schematic diagram of angular velocity state feedback control structure with a two-layer offline tuned neural network is shown in Figure 5. The approximated coefficients are presented in the top part of Figure 5. It should be noted that nonlinearities in this particular case come from the inductance characteristics of the motor. More detailed information related to the synthesis process of the controller and the training process of the neural network approximator can be found in [54].

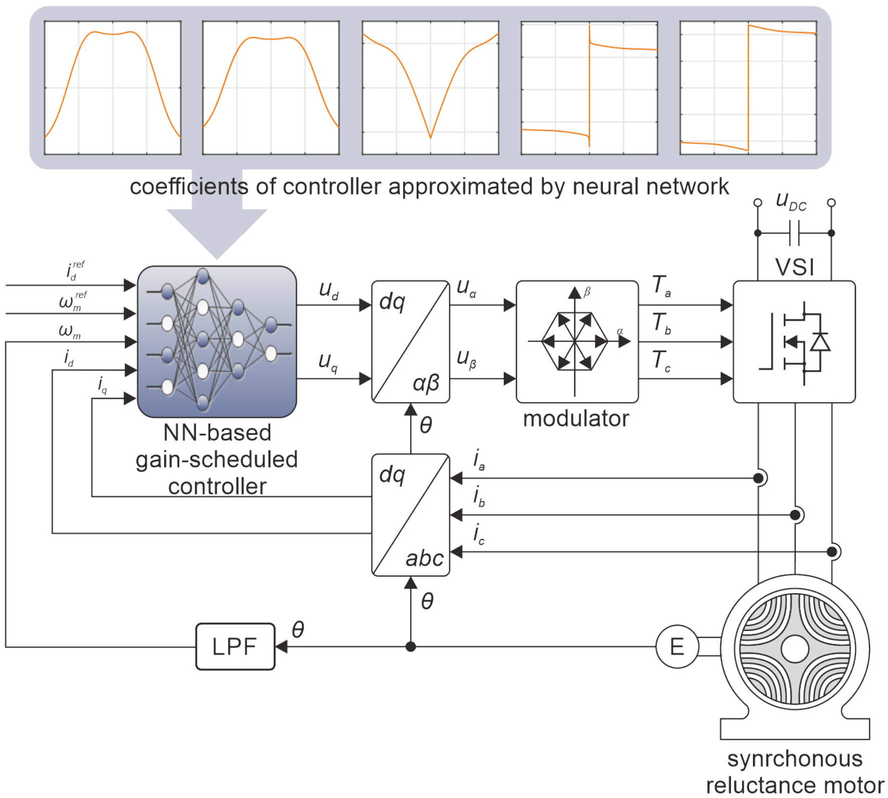

Figure 5. Gain-scheduled neural network-based speed control for synchronous reluctance motor.

As shown in Figure 6, the proposed solution assures high control performance and robustness against parameter variations. In the case of angular speed and *d*-axis current, slight changes caused by a mismatch of the *d*- and *q*-axis inductances are observed in transient, where load torque is imposed and removed. The impact of inductance variations on the *q*-axis current is greater, resulting in different steady-state levels. Although the complexity of a neural network-based solution is 60% higher than a LUT-based solution, it requires fewer memory resources to assure satisfactory accuracy. Due to this, it is expected that the application of neural network-based approximators in high-performance electrical drives will increase.

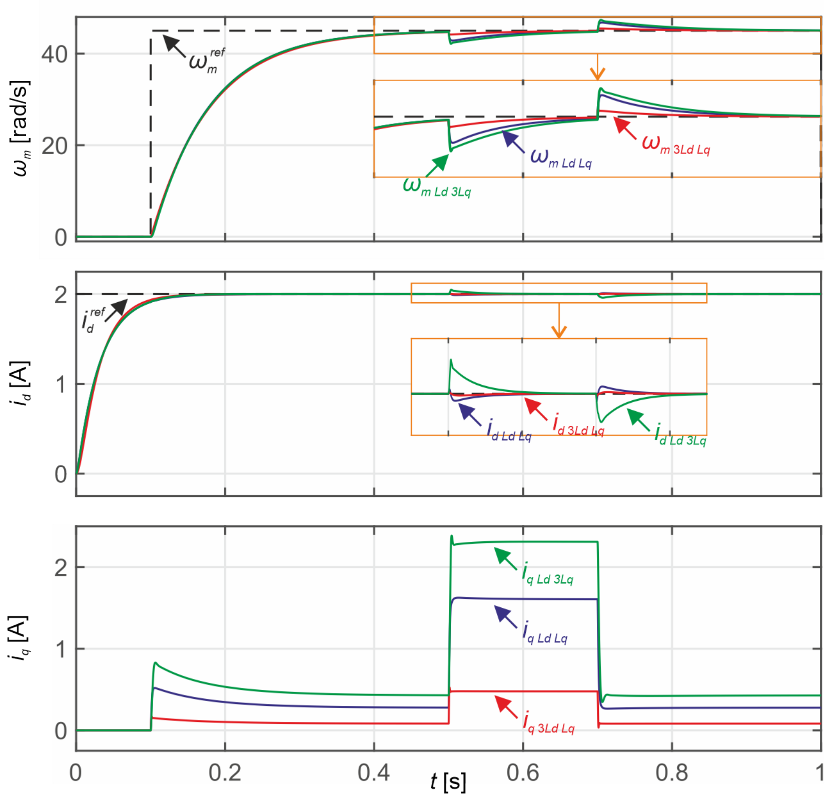

Figure 6. Angular velocity reversal transients of synchronous reluctance motor drive with neural network-based gain-scheduled state feedback controller.

As mentioned earlier, the neural network can be successfully applied as a multiparameter adaptive model. In this case, based on the minimization of the objective function—which is most often related to the definition of the error of the controlled state variable—and then tuning the weights of the neural network, it is possible to obtain a control signal that forces the object to follow the reference signal regardless of disturbances. Various schemes of control structures with neural controllers are used: direct control, indirect control, with an internal model, etc. However, the most common construction uses a reference model [55]. The overall concept for the simplified representation of the electrical drive with adaptation path is shown in Figure 7.

Several elements are described using the expressions presented below:

$$G_r(s) = \frac{\omega_r^2}{s^2 + 2\zeta_r \omega_n s + \omega_r^2}, \tag{9}$$

$$G_T(s) = \frac{1}{T_e s + 1}, \tag{10}$$

$$G_M(s) = \frac{1}{T_M s}, \tag{11}$$

where ω_r is a reference resonant frequency, ζ_r is a damping coefficient, T_e is the total time constant of the loop related to electromagnetic torque, and T_M is the mechanical time constant. The introduced element aims to shape the signal's dynamics (using parameters: ω_r and ζ_r) introduced for the algorithm's calculations, which updates the weights of the neural network. The assumption is to adjust the transients' changes with the controlled object's capabilities. In the results, the output and input variables (e.g., angular velocity) converge, and further weight changes are suppressed (stable operation of the control system).

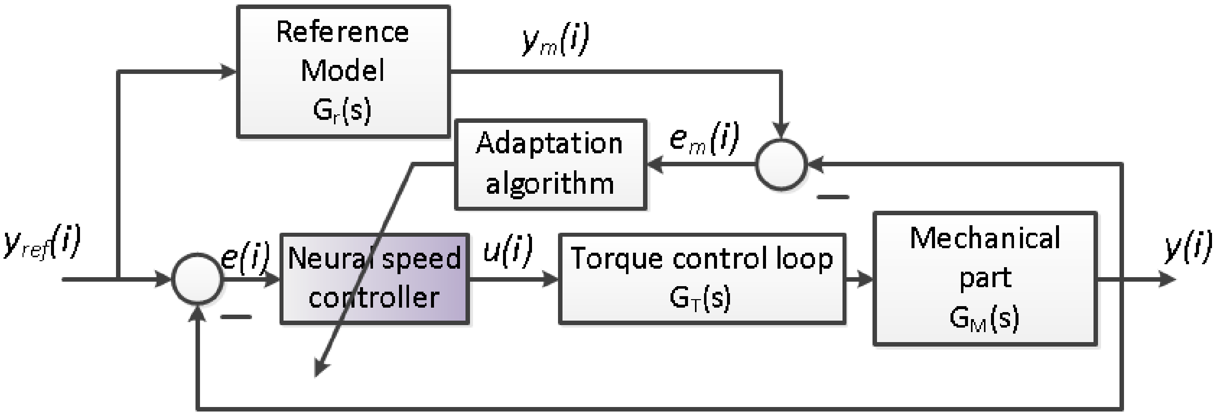

Figure 7. Adaptive control structure with reference model.

The main tunable element in the adaptive control structure can be a simple ADALINE-type model [56]. With this assumption, the calculations are simple, but only a few parameters shape the control signal. An extension of the above solution is a controller based on an MLP neural network with sigmoidal activation functions [57] or the implementation of a radial basis function neural network where an additional adaptation of the centers, apart from the weights, is applied [58]. It should be noted that these models process data in one direction. A better solution seems to be, in the case of time-dependent data analysis, a network application with internal feedback (recurrent neural network), which introduces additional information (from previous samples) through a characteristic structure when the output signal is determined [59].

The models listed above can be used in a cascade connection as an internal current controller or in an external speed loop. The characteristic properties of electrical machines can argue for other applications. For example, drives with PMSM machines can generate significant oscillations observed in electromagnetic torque waveforms, resulting in additional disturbances in the angular velocity [60]. The neural network can be used as an efficient torque ripple compensator [61]. Because the number of PMSM-based drives in the industry is increasing, further development of solutions similar to those presented in [62,63] is expected. In addition to implementing neural networks as controllers, applications of the so-called hybrid controllers has become a future solution. In this approach, neural models will be used in parallel to classical solutions (i.e., PI controller, predictive controller, and state feedback controller). According to this assumption, the system works properly in the presence of disturbances or combines the advantages of different control techniques, as shown in [64–66]. Besides compensation and control signal shifting, the output values of the neural networks can be directly applied as gains in classical controllers. The structure of the main controller remains unchanged, but neural adaptation updates the coefficients to improve the precision of control [67,68]. The analyzed controller can be considered to be a partially adaptive one. In [69], the application of the constant path with the error signal is combined with an integrator updated using the radial basis function neural network. An additional data processing in the control algorithm's path flow seems useful in modern electrical drives. For example, predicting the measured state variables in the adaptation law leads to the accelerated calculation of the speed controller parameters. In the results, the improved shape of the control signal ensures the rapid reaction of the object [70]. Filtering the measurement signals in drives without difficult designs and determining the cut-off frequency can be done automatically using ADALINE. Such an approach was tested for extracting current components and calculating the angle in the compensation system in a drive with a BLDC machine [71]. The summary of the tasks based on neural networks in control structures is presented in Figure 8. The next section considers the issues related to the calculations of signals used in electrical drives.

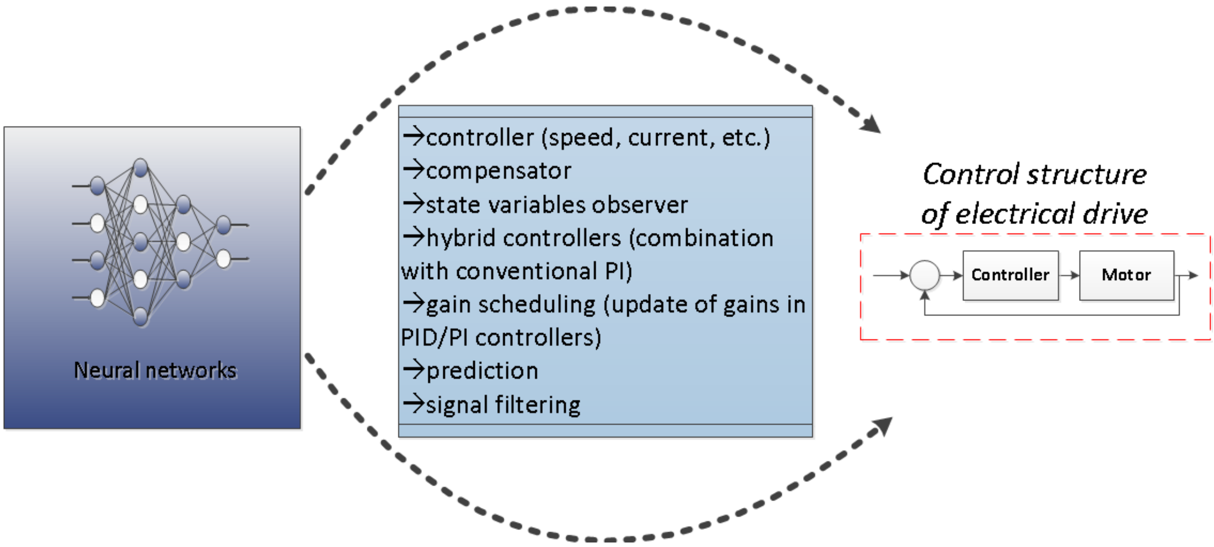

Figure 8. Tasks\challenges for neural networks in control structures of electrical drives.

The individual steps in designing a neural model for an electric drive can be considered universal (i.e., without a direct connection to the task performed). The most characteristic actions are listed in Figure 9. The main goal determines the system's overall structure based on a neural network. The type of network and the method of calculating model coefficients (e.g., weights or centers) should be selected for a specific task. One of the most important points in the designing process, which combines theoretical considerations and practical aspects, seems to be stability analysis. The stability of a class of time-varying adaptive controllers based on neural networks has been analyzed using Lyapunov methods [72–74]. The whole concept focuses on analyzing the initially selected positive definite function. The equation, combined with the object's state variables, leads to a conclusion on the stability if its derivative is negative (12)–(14). The constraints for learning parameters or weights are considered. This assumption ensures the algorithm's convergence in the subsequent steps of the method that calculate the coefficients in the neural model.

$$V(x,t) > 0 \tag{12}$$

$$V(0,t) = 0 \tag{13}$$

$$\dot{V}(x,t) \leq 0 \tag{14}$$

The adaptive neural controllers contain constant parameters (training coefficients, scaling gains, momentum, etc.). The exact determination of those values is difficult or ambiguous. On the other hand, the right selection is very important, because it affects the convergence of the adaptation algorithm (i.e., the time of controller tuning). In such cases, metaheuristic optimization algorithms can be used [53,75]. The initialization process of the neural model is also crucial, because the optimizer's starting point is determined, affecting the generated control signal. Even when the algorithm converges, oscillations of the state variables can occur. In practice, this corresponds to a clutch shudder. Therefore, the risk of mechanical parts being damaged is increased. The issue is also important during experimental tests of the control systems, because randomly determined weights results in different behaviors in the developed controller. The initial training of the neural network has been proposed to overcome this issue. Solving this problem in direct connection with the object's parameters in the expected theoretical work may be useful.

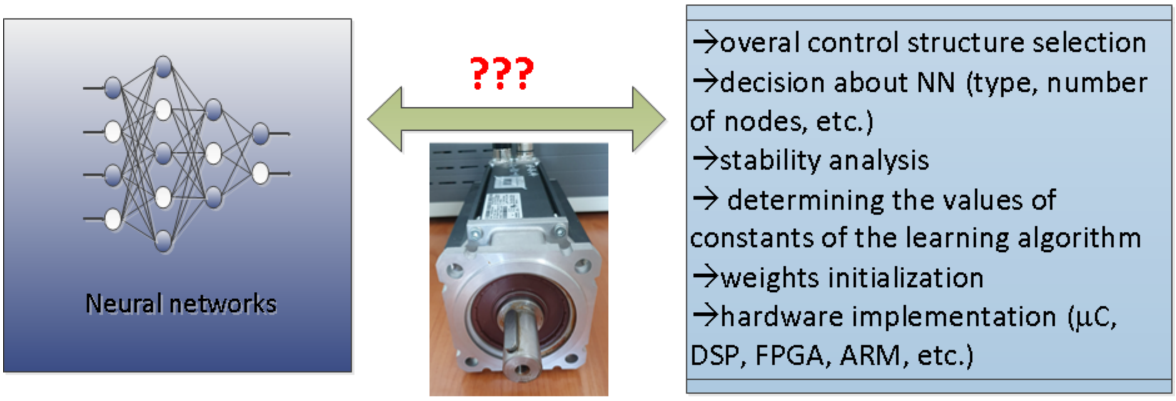

Figure 9. Issues related to neural controller design.

Among the issues related to the control of electrical drives, there is an upward trend in the use of adaptive neural controllers for systems with complex mechanical parts. Reconfigurable models can adapt settings to follow changes in object parameters (inertia, mechanical time constants, friction torque) or operate on the 'model-free' principle (the coefficients are not identified directly) [76–78]. Thus, the application of neural algorithms considered in a specified context of an application, not only for a separate drive operation, is expected in future work.

2.2. State Variables Estimation Based on Neural Networks

Novel control techniques, especially applied to complex objects, often use additional signals from the object. Thus, the number of sensors in the system is increased. This situation is not preferable due to the higher costs of the drive, risk of faults, problematic expansion of the construction size, and issues related to installation. In connection with the above-mentioned drawbacks, appropriate algorithms have been developed, tested and applied, which enable the estimation of signals in control systems. Sensorless systems are based on the following methods of estimation:

- Algorithmic methods;
- Hybrid combinations of classical observers with artificial intelligence methods;
- Signal processing approaches (with neural networks).

The first group of speed estimators is based directly on the mathematical model of the electrical machine. The correct definition of the motor parameters after entering the appropriate values of the gain matrix allows obtaining accurate information about the selected state variables. However, it is difficult to include non-linear phenomena (e.g., friction components) in the calculations. It is often assumed that the object is linear and the parameters are constant in time. Currently, solutions based on (i) model reference adaptive systems (MRAS) [79–83], (ii) Kalman filters [84,85], and (iii) and Luenberger observers [86,87] are applied in electric drives. Here, robustness against parameter mismatch is partially obtained.

To mitigate the impact of parameter discrepancy on estimation performance, a solution based on the hybrid combinations of classical observers with artificial intelligence methods is proposed. In this approach, a connection of neural networks trained online and known algorithmic techniques is utilized [88–90]. The latter component in the hybrid solution can be a typical method known from the control theory (e.g., Luenberger observer). The overall construction is simple, but the precision of the state variables calculation is highly dependent on the precision of the object identification:

$$\frac{d}{dt}\hat{\mathbf{x}}(t) = \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{L}[\mathbf{y}(t) - \hat{\mathbf{y}}(t)], \quad (15)$$

$$\hat{\mathbf{y}}(t) = \mathbf{C}\hat{\mathbf{x}}(t). \quad (16)$$

where $\mathbf{A}$ represents the state matrix, $\mathbf{B}$ is the control matrix, $\mathbf{C}$ is the output matrix, $\hat{\mathbf{x}}$ represents the results of the calculations (vector of state variables), $\hat{\mathbf{y}}$ is the output of the observer (state matrix), and $\mathbf{L}$ is the coefficients defining the arrangement of the poles of the system. The above-mentioned problem is related to elements of matrices (parameters of the electrical machine) (15) and (16). Therefore, to improve the precision, the elements of $\mathbf{A}$ and/or $\mathbf{B}$ are achieved from the neural network. In other solutions, gains of the observer $\mathbf{L}$ are under constant adaptation [91].

A different type of observers assumes data processing and direct analysis of the dependencies between the measured signals. This challenge can be achieved using neural networks. The models can reproduce the relationships between input and output data based on weights previously defined in the training process. In this way, data transformation is obtained, and as a result, a new signal is generated. It is expected that the described approach will be used in modern electrical drives for estimation purposes.

Assuming three state variables available for measurement, it is possible to replace one sensor with a neural estimator. A specific example is presented in this section for an electrical drive with an elastic connection between machines (motor and load). The aforementioned design of the mechanical part of the drive can lead to oscillations of state variables, which makes precise control difficult. The control systems used for vibration damping (e.g., PI controllers or state feedback controller) use an increased number of feedbacks, as shown in [92]. There are two different speeds (ω_1, related to the motor and ω_2, related to the load) and shaft torque m_s in the system used as information for the controllers, as presented in Figure 10. In this task, a recurrent neural network trained offline (i.e., based on previously collected measurement samples) is implemented. A model with a context layer is considered namely the Elman network. The following inputs of the estimators are selected: the electromagnetic torque m_e and the motor speed ω_1. The goal is to estimate the load speed ω_2 and the shaft torque m_s. The training was performed according to the Levenberg–Marquardt algorithm (1000 epochs). Both networks contain 10 hidden nodes. Details of the neural estimator design are described in the paper [93].

The drive performs cyclic reversals (i.e., the direction of rotation is changed after 2.5 s). In the steady state, the speed value is set to 20% of the nominal one. The obtained results show the high precision of the operation of neural estimators. The calculations are independent directly from the mathematical model of the object (only transients are used). This means that neural estimators are expected to be resistant to parametric disturbance. The design process is also simplified (e.g., identification of parameters is not necessary). Moreover, using a high-level programming language, the hardware implementation is not complex. The observed measurement disturbances (noise) do not significantly affect the estimation performance. The results presented in Figure 10 do not take into account the active action of the load. Thus, in the subsequent test, this condition is analyzed in Figure 11. It can be seen that the quality of the signal observation is still very high. Networks very accurately calculate state variables in the presence of dynamic changes in the input values.

It is expected that techniques presented in this section related to the estimation of state variables in electric drives will be developed due to the challenges that still arise. An example of this may include new types of electrical machines with higher efficiency and reliability and modifications to the existing machines. In addition, the compound structure of the drive actuators may be another reason for the application of precise and robust estimators. Moreover, the number of observers applied to diagnostic issues increases. The above tasks are additionally supported by available tools, modern industrial controllers, and libraries that ensure rapid implementation of the algorithms. This tendency also takes into account neural networks, which are becoming a very important element due to the guarantee of facilities (software and hardware) and possibilities to overcome the limitations of conventional observers.

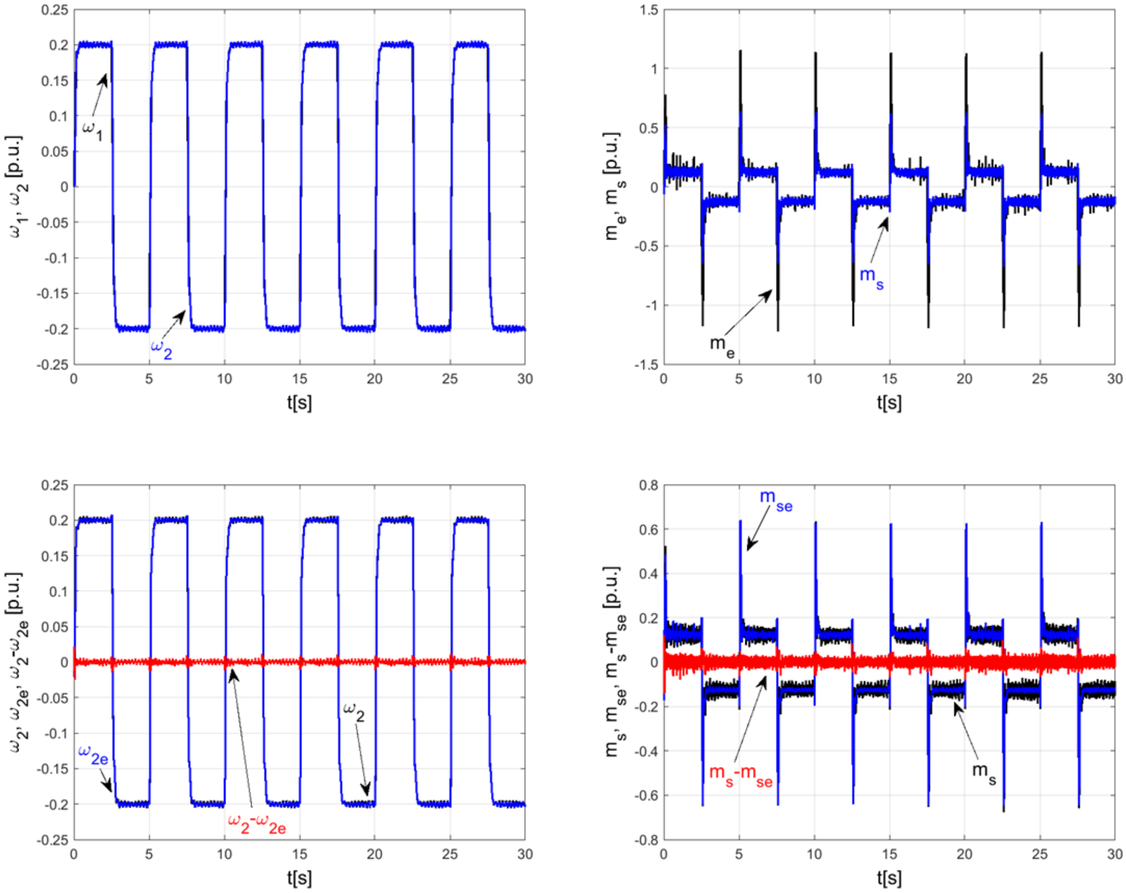

Figure 10. State variables—real and estimated (with subscript 'e') using a neural network—of two-mass system (ω_1—motor speed, ω_2—load speed, m_s—shaft torque, m_e—electromagnetic torque).

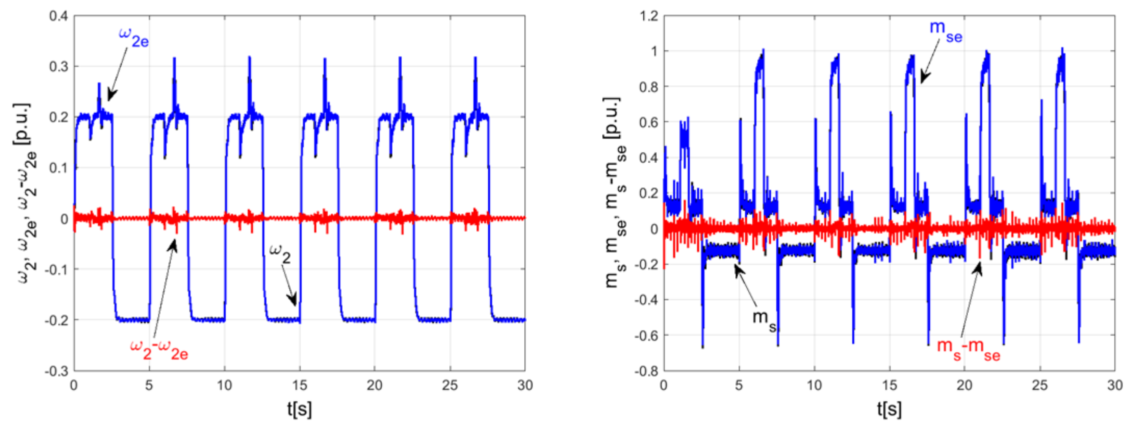

Figure 11. Estimation of state variables in two-mass system: load speed ω_2 and shaft torque m_s using the recurrent neural network (load imposed).

2.3. Concepts of Neural Network Applications in Power Electronics

The power electronics converter is the main part of the modern electrical drive [94–96]. The converter properties, such as high efficiency, high reliability, high power density, and low harmonic distortion, directly impact the electrical drive features. For this reason, improving power electronic converters' behavior is still crucial in this field of application. The future progress of power electronics converters supported by neural networks is expected to be observed in the following areas: (i) modeling and optimization of components, components arrangement, and thermal investigations; (ii) reliability of power converter components and sensors; and (iii) harmonics reduction and control performance improvement. A schematic diagram of the power converter with marked areas of neural network-based improvements is shown in Figure 12, and the above-mentioned areas are described in the following subsections.

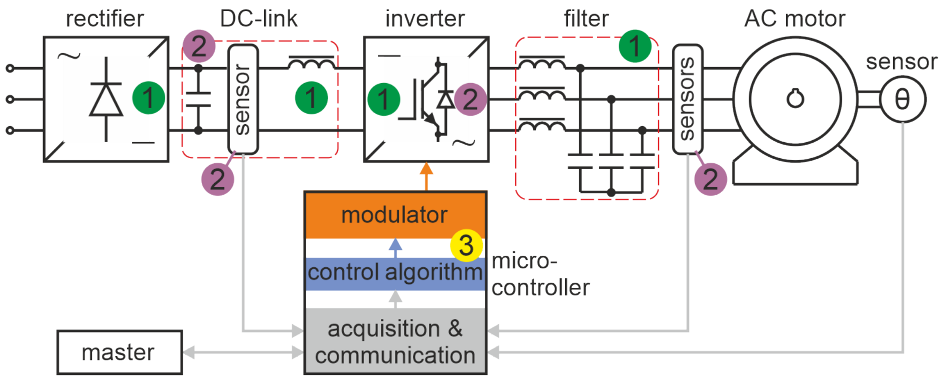

Figure 12. Schematic diagram of the power converter with marked areas of neural network-based improvements: (1)—modeling and optimization of components, components arrangement, and thermal investigations, (2)—reliability of power converter components and sensors, and (3)—harmonics reduction and control performance.

2.3.1. Modeling and Optimization of Components, Components Arrangement, and Thermal Investigations

The topology, component selection, optimization, and arrangement are challenging and are typically an iterative design process [97]. On the other hand, a multi-objective optimization gives very promising results, resulting in a solution with $\approx 15\% \div 20\%$ higher power density and a 1.7% higher efficiency at 2 kW rated power [97]. The designing process of a power converter must consider several specifications, including component arrangement with air ducts for cooling, the total volume of a cooling system, and the size reduction of passive components. As shown in [98,99], a multidisciplinary optimization supports virtual prototyping of components arrangement and passive components sizing (e.g., inductors, capacitors) considering mass, losses, and volume minimization. Because designing passive components and filters applied in power converters require modeling and optimization, neural network-based optimization tools are expected to improve this procedure, decrease the time, and improve the engineers' experience. Preliminary results show that a deep symbolic optimization framework can successfully support the power converter's development process, resulting in increases in efficiency [99]. Inductor modeling and optimizing processes can also be made using an ANN-based approach, as shown in [100]. The proposed workflow generates the magnetic and thermal data from FEM simulations and designs inductors using ANNs. Several parameters, such as geometry, mass, and losses, are considered. The successful optimization depends on the proper selection of ANN (i.e., number of layers, number of neurons,) the training method, and signal preprocessing. The development of described approach is expected to mitigate the identified drawbacks, i.e., the increased complexity and dataset availability [100]. The modeling and optimization procedure supported by ANN has also been applied to improve the EMI filter design [101]. The authors show that a partly connected ANN can accurately simulate the insertion losses of the filter. Moreover, the training process is faster for the developed architecture than typical multi-output ANN. A drawback of this solution is related to a complex performance function with several components and parameters.

Future improvement is expected to provide more intuitive performance indexes with a limited number of coefficients to set. Effective optimization of magnetic components for power converters requires proper modeling in electromagnetic and thermal domains [102]. Currently, the most accurate models are obtained using 3D FEA simulations. This approach is time-consuming due to the mesh requirements. In [102], a two-level homogenization technique was proposed to significantly reduce the analysis time. Future improvement is expected to be based on an approach similar to [103], where a convolutional neural network has been applied to predict the thermal properties of the power semiconductor package. Because the heat flux affects the performance of the power semiconductor package, it is important to predict the thermal properties according to the pattern. As shown in [103], an algorithm based on a convolutional neural network successfully learns the pattern characteristics from a PCB image to identify the local effective thermal conductivity. The proposed solution provides much more accurate results than the reference solutions [103]. Prediction based on artificial neural networks can also be used to improve the heat transfer performance of the liquid-based heat sink [104]. Such a solution can enhance the performance of commercially available heat sinks thanks to the prediction of the PCB temperature under various operating conditions. The proposed solution considerably reduces the PCB temperature thanks to the ANN learning and generalization abilities.

2.3.2. Reliability of Power Converter Components and Sensors

The proper and safe operation of an electrical drive requires accurate measurements of several electrical and mechanical signals (i.e., phase currents, DC link voltage, angular position) [94,95]. Hardware redundancy improves system reliability and increases the power converter's cost and overall volume. Diagnostics of measurement devices can be made using algorithms and signal analysis [105]. In this approach, features important for diagnostic evaluation are extracted from signals. As depicted in [106], the application of artificial intelligence assures better evaluation and more diagnosis possibilities with reduced expert knowledge. It should be emphasized that the Levenberg–Marquardt learning algorithm applied is time-consuming, and the extension of this solution should be the reference base with neural detectors initially trained for different control algorithms (e.g., direct torque control) and several kinds of current sensor faults. An optimized classifier based on the convolutional neural network can also indicate switch faults in the power converter [107]. After denoising and manual tuning, the proposed approach accurately identifies known faults and can also distinguish unknown faults. Future works in this field should address the limitation of manual tuning and the elimination denoising process. The latter can be made automatically [108]. It is also expected that a digital-twin concept shown in [109] will be developed for the reliability assessment of power converters. In this approach, multi-physics simulations of power semiconductor components are used to simulate reliability, and a machine learning scheme is applied to prognosis future behavior. Such a hybrid solution is recommended for new technologies with limited data sets. In voltage source inverters commonly used in electrical drives, the failure may also come from the DC link capacitors. Therefore, their condition should be monitored in terms of power converter reliability. This task can be considered using the artificial neural network to estimate the capacitance value, as shown in [110]. An extended version of this approach should reduce the estimation error and consider transient conditions.

2.3.3. Harmonics Reduction and Control Performance Improvement

To provide a better control quality (i.e., reduction in electromagnetic torque ripple, mitigation of noise, minimization of harmonic content), multilevel voltage source inverters are applied in high-performance electrical drives [111]. Because several power semiconductor switches are used in this converter, an advanced and computationally efficient modulator is required. The considered tasks can be accomplished using neural-network-based modulators, as described in [112,113]. ANN's classification ability is utilized to quickly and accurately select the space vectors and their duty cycles. The proposed concept has been extensively investigated in experimental tests [112,113]. The obtained results and developed principles give a perspective for applying these kinds of modulators in inverters with high levels in the future. As shown in [114], ANN can mitigate the harmonics level in a two-level H-bridge inverter. In this approach, a conventional current controller is replaced by a neural network one, reducing THD by 5%. Although simulation results are shown in this work, the proposed solution is expected to be implemented in applications soon.

A perspective of power converters development supported by artificial intelligence is also correlated with high-performance control schemes. Recently, model predictive control (MPC) has gained attention due to its simple and intuitive model-based implementation and better control characteristics compared to classical linear control approaches [115–117]. The main drawbacks of the considered control lie in computational complexity and accuracy. As shown in [117], a significant resource requirement reduction can be achieved for ANN-based MPC. The ANN is trained offline using the same input signals as the MPC controller. Next, it generates control signals for each power semiconductor. Because of its simple mathematical expression and approximation capacity, the computational burden of ANN-MPC is reduced compared to the reference solutions [117]. The experimental results indicate the potential of the described solution. Because the performance of MPC mainly depends on the quality of the prediction model, future work in this field will be concerned with robustness against unpredictable parameter variations. The generalization ability of ANN is a key feature in this task. Designing MPC requires the selection of the cost function to be optimized. It usually consists of several components and weighting factors [116]. Because selecting the latter ones is non-trivial, an ANN approach has been proposed to automate this process. Moreover, the synthetic cost function was replaced by a more intuitive formula with a total harmonic component and switching frequency of power converter [116]. The MPC with ANN-supported cost function shows good tracking performance and fast optimization. An expected direction of future work could be an extension of ANN-based MPC for cascade-free control of electrical drives, where torque and angular velocity are simultaneously controlled using the predictive approach. Because the more complex performance index will be optimized, the ANN-supported concepts described above should provide a relatively simple cost function, mitigation of computational complexity, and superior performance and robustness.

2.4. Neural Networks in Diagnostics

An analysis of scientific publications and available engineering reports indicates a constant search for diagnostic tools that include the continuous monitoring of electrical drives, quick detection of damage, and assessment of the degree of the problem. Detection of the initial stage of faults allows: (i) the protection of the environment against potential danger, (ii) the occurrence of more serious (extension) failures and related costs, and (iii) a plan of renovation [118]. The purpose of this section is not to conduct a detailed analysis of diagnostic systems, but to indicate the increasing number and the importance of neural networks as a tool used in them.

Currently, the applications of diagnostic solutions for electrical drives with induction motors and permanent magnet synchronous motors are dominant. It is related to many applications of mentioned machines in industrial implementations. This is due to the properties of these machines: wide range of operation (speed), simplified installation (size), high dynamics (reduced inertia), and acceptable overload. The most common damages concern the basic components of the electrical drive: machines, power electronics devices, and sensors. The issues concerning the machines are focused on the stator (winding) or rotor faults (bearing, misalignment, eccentricity, imbalance) [119,120]. The main problems appearing in power converters are damage of semiconductors (short-circuit and open-circuit faults), intermediate segment (filter capacitors), or events resulting from the wrong operation or improper implementation of the device [121–123]. The last part of the issues is mainly due to damages to the current sensors or encoders [124–126]. The cases related to the reliability of power converters and sensors are mentioned earlier in Section 2.3.2.

The classification of diagnostic methods for electrical drive faults contains three main classes (listed below).

- Generating (and analyzing) diagnostic symptoms based on physical signal measurements.
- Application of methods known from control theory and electric machines fundamentals.
- Implementation of artificial intelligence algorithms.

The strategy, often adopted in the first category of diagnostic methods, can be a scheme of a typical failure detection procedure. Several parts are presented in Figure 13. The occurrence of a fault in the electric drive is observed by changes in the physical signals that are measured in the system. State variables easily accessible by measurement, such as current or vibration, are often analyzed. However, the changes are not directly visible to the user. Therefore, in the next step, appropriate transformations (fast Fourier transform, symmetrical component analysis, principal component analysis) are applied to highlight abnormalities. Then, the assessment of the symptoms is conducted. For this purpose, neural networks are applied. The other group of methods is based on the analysis of the reference model and real signals from the drive. The methods used for object representation are utilized in this task (finite element methods, circuit models, state observers, etc.). However, there is still a problem related to the ambiguity of the results and their evaluation (it is overall task appearing in diagnostics of engineering systems) [127]. Thus, the whole system combines neural networks (used as detectors). As a special case in this category, the use of fault-tolerant control algorithms can operate under technical problems of the drives (adaptive control, switching structures, applications of the compensator, etc.). The last solution assumes the direct use of neural networks to analyze the fluctuations in the measured signals [128]. This approach facilitates the calculation process and eliminates problems with signal processing (e.g., distortions in current components).

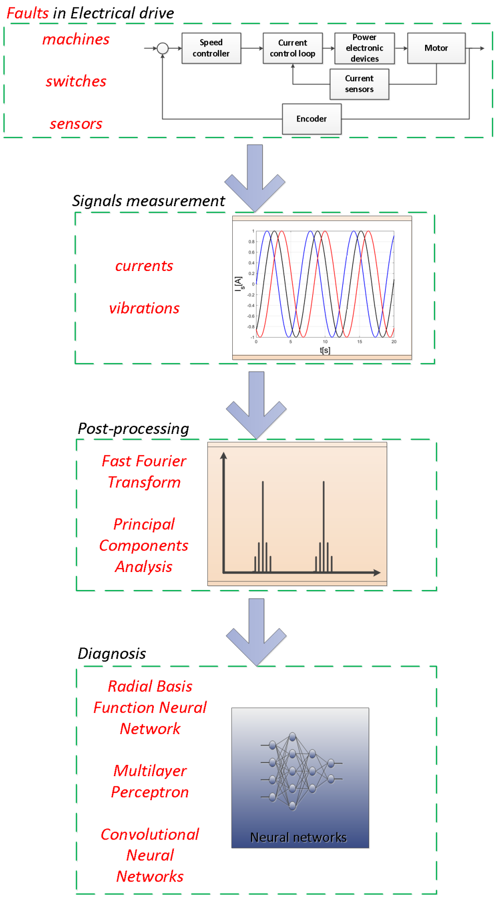

Figure 13. Common stages of diagnostics process.

It should be emphasized that efficient diagnostics and monitoring of the electric drive condition not only leads to reduced operating and damage costs (e.g., downtime of the system in the industry) but, above all, ensures the safety of users and operators of automation systems. Therefore, due to the importance of the issue, the diagnostics of electric drives based on artificial intelligence algorithms will continue to be developed. Recently, a multi-granularity neighbor residual network has been proposed for anomaly detection in time series data [49]. In this structure, linear and nonlinear feature extraction paths are separated and feature extraction of different granularity is made after the initialization phase. Finally, parameter optimization based on residual features and abnormal probability identification is performed. The considered solution shows good performance on precision during optimization evaluation and outperforms reference models such as a generalized linear classifier a multilayer neural network with both linear and non-linear transformation. Because this type of neural network can effectively capture the feature of samples in time series data and predict the abnormal probability of the sample, it is expected that the considered approach will be adopted to monitor and diagnose electrical drive in terms of sensors and power stage components.

Neural networks are used in all the diagnostic methods briefly described above. It can be expected that neural networks will still be an important element of diagnostic systems. The extension of classical analysis leads to significant benefits, and the most important are the following:

- Neural networks are tools improving the simplification and efficiency of drive condition monitoring;
- Higher precision of faults detection is achieved;
- The time to problems recognition is shortened;
- Automation of the analysis of a complex data set;
- The ability to reduce or eliminate mathematical modeling;
- Robustness against measurement disturbance is achieved;
- Neural networks are easy to implement using available tools (software and hardware).

3. Discussion

This section indicates possible challenges of applications for neural networks in electrical drives. These are identified in data, hardware, and methodology.

In the case of data, the following challenge can be pointed out. Because the learning process is based on data collection, providing an accurate and representative set of signals for the neural network's weights optimization and validation is crucial. This challenge can be addressed by using a repository with collections of data and pre-trained neural networks. Such a solution is recently found in medicine, vision, and agriculture. It is expected that relevant repositories will be created for electrical drive applications for control, estimation, diagnostics, and construction purposes. Effective use of pre-trained nets and collections of data depends on proper description and documentation; therefore, the development of hosting platforms similar to GitHub is also expected. On the other hand, further improvement of data generalization methods will also be useful to address challenges related to data availability and quality.

Because the time available for execution of control algorithm in modern electrical drive is relatively short (62.5 ÷ 100 μs for drives with IGBTs and even 45 μs for drives with SiC MOSFETs), implementation on online learning neural network is challenging task from the hardware point of view. To overcome this issue, a control board with a combination of DSP and FPGA or powerful research and development controller board is utilized. It is expected that solutions from other fields will be applied to solve complex and computationally demanding tasks. As an example, mobile robotics can be pointed out, where powerful master controllers with specialized software (e.g., NVIDIA Jetson with a robotic operating system) are introduced to provide necessary resources and to unify the methodology.

The last challenge is related to the methodology. Because of the specific applications and hardware demands listed above, topologies of neural networks and learning methods differ from applications in vision systems and medicine. The classical control approach in electrical drives is based on a cascade control structure with PI controllers and Luenberger observers. Here, tuning methods such as an internal model principle, pole placement, and symmetric optimum criteria are utilized. In the case of NN-based control and estimation, there are no specified and well-known solutions. Here control parameters are usually selected using a trial-and-error approach that is time-consuming and may result in a non-optimal structure or operation. A similar situation occurs if the learning process is supported by metaheuristic optimization algorithms. It is expected that the above-mentioned challenge will be addressed by developing a set of rules and guidelines useful for engineers.

4. Conclusions

The paper presents an analysis and a perspective of neural network applications in electrical drives. Based on the available publications, it can be seen that it is a rapidly growing area. Due to the availability of efficient algorithms and appropriate and relatively cheap hardware tools, this trend can be expected to continue. Industrial development, which introduces the need for new technologies, also allows us to predict the use of artificial intelligence methods in modern electrical drives. The perspectives related to the implementation of neural networks in electrical drives are listed below:

- Faster calculations to provide a rapid and precise reaction of control algorithms (code optimization and new software/hardware solutions);
- Hardware developments enabling deep learning-based diagnostics;
- Subsequent development of soft computing algorithms to improve the application of neural networks in handling time-varying problems;
- Applications of deep learning techniques in control of electrical drives forcing an accurate reference transient tracking;
- Hardware accelerations support (i.e., improved and faster calculations) for deep learning methods using new libraries of programming languages (e.g., Python, Java, C++);
- Adaptive control methods used for nonlinear, partially identified, and time-varying systems;
- Neural models of complex systems with electric drives using deep learning to reduce complex mathematical description;
- Increase the number of drive constructions in which neural algorithms will be calculated in parallel using the FPGA;
- Development of hardware modules in programmable devices supporting neural networks implementation and training,
- Application of new types of neural networks currently being developed in theoretical work (e.g., graph neural networks);
- Hybrid combinations of neural networks and models based on expert knowledge (e.g., fuzzy logic) in diagnostics and control;
- Application of metaheuristic methods for parameter selection to improve algorithm convergence and robustness;
- Optimization of topology, heat exchange, and component development and arrangement to improve the efficiency and reliability of power converters.

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