Innovative Methods for Control of Electric Vehicles

Gergana Vacheva [1], Nikolay Hinov [1], Bogdan Gilev [2]

[1] Technical University of Sofia, Department of Power electronics, blvd. Kl. Ohridski, 8, Sofia, Bulgaria
[2] Technical University of Sofia, Department of Mathematical Modelling and Numerical Method, blvd. Kl. Ohridski, 8, Sofia, Bulgaria

***Abstract* – In the current paper is presented an examination of the innovative methods for control of electric vehicles. Principal characteristics of linearization of nonlinear system, model predictive control and neural network are proposed. The main objective of this research is to determine the important advantages and disadvantages of the different approaches for control.**

***Keywords* – electric vehicles, linearization, model predictive control, neural network.**

1. Introduction

Recently, with increasing usage of electric vehicles (EVs) in daily routine, the problems connected with control methods have become more interesting for multiple researchers.

A significant problem that predisposes the development of the EVs is the severe reduction in oil reserves. World oil consumption is steadily increasing and cannot be compensated. Accordingly, it leads to an increase in its price and a strong dependence on the countries where it is extracted. For these reasons, it is important to find a new technological solution in order to reduce this consumption.

DOI: 10.18421/TEM91-02
https://dx.doi.org/10.18421/TEM91-02

Corresponding author: Nikolay Hinov,
Technical University of Sofia, Department of Power electronics, blvd. Kl. Ohridski, 8, Sofia, Bulgaria.
Email: hinov@tu-sofia.bg

Received: 15 December 2019.
Revised: 22 January 2020.
Accepted: 28 January 2020.
Published: 28 February 2020.

The most used energy sources in these technologies are batteries, supercapacitors, fuel cells, and others [1], [2].

For solving these problems in the transport, it is necessary to take actions. The use of EVs as electric bicycles, trams, electric buses and trains can significantly reduce carbon emissions. This solution involves the use of innovative control strategies for management of energy flows in the EVs.

The structure of this paper is organized as follows: linearization of electric vehicles' model – basic definition, determination of the operating points and linearization of a nonlinear model; model predictive control - determination of the main characteristics of this type of control and definition of the constraints; control with neural network – operation of the NARMA controller and typical structure.

2. Linearization of the Model of Electric Vehicles

The bigger part of the system for control consist of negative closed loop. An example for this type of system is proposed in Figure 1.

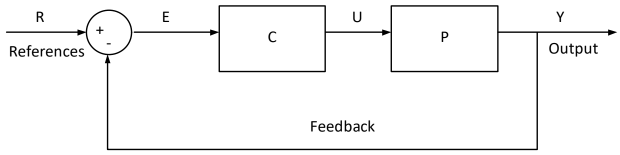

Figure 1. Control system with feedback loop

The presented model is in equilibrium operation point. Taking into consideration the linearization of the plant P, the input U and the output Y can be changed in small region. The part of the system which can be linearized is presented in Figure 2.

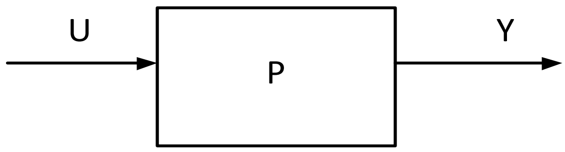

Figure 2. Part of linearization system

However, due to the presence of a feedback loop, the changing of the output signal will go back to the controller C and then to the plane. This affects the behavior of the system. In fact, if *C* and *P* were linear, the lairized model between *U* and *Y* would be equal to $\frac{P(s)}{1+C(s)P(s)}$, rather than *P (s).*

The feedback loop can be removed from the model to resolve this problem. However, as shown in the following Figure 3., this changes the operating point of the system since the error signal *E* is now equal to the set signal *R*. Linearization around this new operating point would change the linearization results. Of course, this only matters for nonlinear models. When the model is already linear, it has the same shape considering the operating point [3], [4].

Figure 3. Control system without feedback loop

For linearization in the MATLAB/Simulink environment, the Control Design tools is used. This tool allows the marking of the input or output as an open loop. This ensures that the output signal is not fed back into the model but maintains the operating point the same. In other words, it is calculated in a linear case P(s), not $\frac{P(s)}{1+C(s)P(s)}$.

Operating Points

The operating point of a dynamic system determines its overall state at a given moment [5], [6]. The level of the operating point influences the behaviour of the system. [7] The linearized model is an approximation that is valid for a small area around the operating point of the system. [8], [9] The following figure shows a nonlinear function $y=x^2$ and linear function $y=2x-1$. The linear function is an approximation to the nonlinear function for the operating point x = 1, y = 1. In the near area to the working point, the approximation is good. Far from this working point, the approximation is bad. The exact boundaries of this region are often somewhat arbitrary [10], [11], [12]. The following Figure 4. shows a possible region of good approximation for linearization of $y=x^2$.

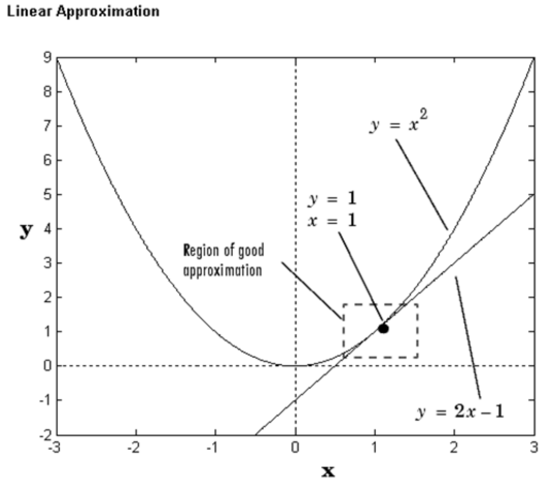

Figure 4. Linear approximation

Linearization of Nonlinear Models

The following Figure 5. shows the block diagram which consist of input signal *u(t)*, measured output signal *y(t)* and nonlinear system, that described the states of the system and its dynamic behaviour P.

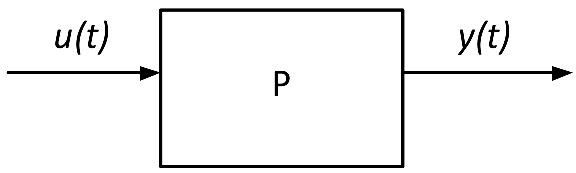

Figure 5. Block diagram

The block diagram can be described with the following equations

$$\dot{x}(t)=f\left(x(t),u(t),t\right)$$
$$y(t)=g\left(x(t),u(t),t\right) \quad (1)$$

where *x(t)* is the state of the system, *u(t)* are the inputs and *y(t)* are the outputs. In these equations, the variables vary continuously over time.

A linear invariant approximation for this system is valid in the area around the operating point at $t = t_0$, $x(t_0) = x_0$ and $u(t_0)=u_0$. If the values of the state of the system *x(t)* and the inputs *u(t)* are significantly close to the operating point, the system will behave approximately linearly [13], [14].

For describing of the linearized model, in the first place it is necessary to define new variables around the operating point of the states of the systems, the inputs and the outputs:

$$\delta x(t)=x(t)-x_0$$
$$\delta u(t)=u(t)-u_0 \quad (2)$$
$$\delta y(t)=y(t)-y_0$$

The values of the outputs in the operating points are definite with $y(t_0) = g(x_0, u_0, t_0)=y_0$.

The linear equations of the state space given by $\delta x(t)$, $\delta u(t)$ and $\delta y(t)$ are equal to:

$$\begin{aligned} \delta\dot{x}(t) &= A\delta x(t) + B\delta u(t) \\ \delta y(t) &= C\delta x(t) + D\delta u(t) \end{aligned} \quad (3)$$

where A, B, C and D are matrix with constant coefficient. These matrix are defined by the system of Jacobian and evaluated in the operating point:

$$\begin{aligned} A &= \left.\frac{\partial f}{\partial x}\right|_{t_0, x_0, \mu_0} \\ B &= \left.\frac{\partial f}{\partial u}\right|_{t_0, x_0, \mu_0} \\ C &= \left.\frac{\partial g}{\partial x}\right|_{t_0, x_0, \mu_0} \\ D &= \left.\frac{\partial g}{\partial x}\right|_{t_0, x_0, \mu_0} \end{aligned} \quad (4)$$

The transfer function of the linearized model can be used in the place of the system P, from the previous figure [7], [15]. For determination of the transfer function it is necessary to separate the Laplace transform:

$$P_{lin}(s) = \frac{\delta Y(s)}{\delta U(s)} \quad (5)$$

3. Model Predictive Control of the Electric Vehicles

For determination of this type of control, the linear system is described with the following equations:

$$\begin{aligned} \dot{\mathbf{x}} &= A\mathbf{x} + B_\beta u + B_v v \\ y &= C\mathbf{x} \end{aligned} \quad (6)$$

The above system is transformed to discrete system in function of time and equal to:

$$\begin{aligned} \mathbf{x}(k+1) &= E\mathbf{x}(k) + F_\beta u(k) + F_v v(k) \\ y(k) &= G\mathbf{x}(k) \end{aligned} \quad (7),$$

where x is a state vector, y is the output of the object and k is the time, v is perturbation.

With the usage of recursion it is equal to:

$$\mathbf{x}(k+j) = E^j\mathbf{x}(k) + \sum_{i=1}^{j} E^{i-1}F_\beta u(k+j-i) + \sum_{i=1}^{j} E^{i-1}F_v v(k+j-i) \quad (8),$$

where j is the time interval for which is determined the predictive control.

The predicted value of the output of the system is:

$$y(k+j-1) = GE^j\mathbf{x}(k) + \sum_{i=1}^{j} GE^{i-1}F_\beta u(k+j-i) + \sum_{i=1}^{j} GE^{i-1}F_v v(k+j-i) \quad (9).$$

It is used in the equation (9), and the vector of the output values of the system output for N_p is designed for the next time interval:

$$\begin{aligned} y(k) &= GE^1\mathbf{x}(k) + GF_\beta u(k+1) + GF_v v(k+1) \\ y(k+1) &= GE^2\mathbf{x}(k) + \sum_{i=1}^{2} GE^{i-1}F_\beta u(k+2-i) + \sum_{i=1}^{2} GE^{i-1}F_v v(k+2-i) \\ &\vdots \\ y(k+Np-1) &= GE^{Np}\mathbf{x}(k) + \sum_{i=1}^{Np} GE^{i-1}F_\beta u(k+Np-i) + \sum_{i=1}^{Np} GE^{i-1}F_v v(k+Np-i) \end{aligned} \quad (6)$$

The system (10) is presented in matrix type and can be described with the following equation:

$$\hat{\mathbf{y}}(k) = C_A\,\mathbf{x}(k) + C_\beta\,\hat{\mathbf{u}}(k) + C_v\,\hat{\mathbf{v}}(k) \quad (11),$$

where

$\hat{\mathbf{y}}(k) = \left(y(k) \ldots y(k+N_p-1)\right)^T$ is a vector of the outputs of the system;

$\hat{\mathbf{u}}(k) = \left(u(k) \cdots u(k+N_p-1)\right)^T$ is a vector of the control signals of the input of the system;

$\hat{\mathbf{v}}(k) = \left(v(k) \cdots v(k+N_p-1)\right)^T$ is a vector of a measurable disturbance signal of the input of the system;

$$C_\beta = \begin{pmatrix} GF_\beta & 0 & \cdots & 0 \\ GEF_\beta & GF_\beta & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ GE^{Np-1}F_\beta & GE^{Np-2}F_\beta & \cdots & GF_\beta \end{pmatrix},$$

$$C_v = \begin{pmatrix} GF_v & 0 & \cdots & 0 \\ GEF_v & GF_v & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ GE^{Np-1}F_v & GE^{Np-2}F_v & \cdots & GF_v \end{pmatrix} \quad (72)$$

and

$$C_A = \begin{pmatrix} GE & GE^2 & \cdots & GE^{Np} \end{pmatrix}^T.$$

At reference control, the vector of the set trajectory is known

$$\hat{\mathbf{r}}(k) = \left(r(k) \quad \cdots \quad r(k+N_p-1)\right)^T \quad (8).$$

The error is defined by

$$\varepsilon_j = r(k+j) - y(k+j) \quad (9)$$

And the vector of the errors in different time interval is presented

$$\hat{\boldsymbol{\varepsilon}} = \left(\varepsilon_1 \quad \varepsilon_2 \quad \cdots \varepsilon_{Np}\right)^T \quad (10).$$

That allows the definition of the following problem for linear programming

$$\min_{(\hat{u},\hat{\varepsilon})} \sum_{i=1}^{Np} \varepsilon_i \qquad (11),$$

With constraints

$$\begin{aligned} C_\beta \hat{\mathbf{u}}(k) + C_v \hat{\mathbf{v}}(k) + C_A\ \mathbf{x}(k) - \hat{\mathbf{r}}(k) \le \hat{\boldsymbol{\varepsilon}} \\ -C_B \hat{\mathbf{u}}(k) - C_v \hat{\mathbf{v}}(k) - C_A\ \mathbf{x}(k) + \hat{\mathbf{r}}(k) \le \hat{\boldsymbol{\varepsilon}} \end{aligned} \qquad (12)$$

$$\hat{\mathbf{u}}_{\min} \le \hat{\mathbf{u}}(k) \le \hat{\mathbf{u}}_{\max} \qquad (13)$$

The constraints (17) ensures that the sum of the errors (16) is minimized by module.

After solving of the problem with the methods of the linear programming the control vector is defined

$$\hat{\mathbf{u}}(k) = \left(\mathbf{u}(k) \ \cdots \mathbf{u}(k + N_p - 1) \right)^T \qquad (19)$$

and the vector of the errors

$$\hat{\boldsymbol{\varepsilon}} = \left(\varepsilon_1 \ \cdots \varepsilon_{Np} \right)^T \qquad (20)$$

With resolving this problem, the value of the control system is determined. The same procedure is applied for finding the next control signal. The control process is repeated until the end of the control time.

In this part is described a typical approach of model predictive control [16], [17], [18]. After the realized linearization, a controller for the control process is proposed in the converters of the electric vehicles. The operating processes in the converters are nonlinear and this type of control is a requirement.

4. Control With Neural Network

In MATLAB/Simulink a model of the nonlinear open system is created (Reference Model). The realized model is used for identification of the object (Plant) with the neural network in Figure 6.

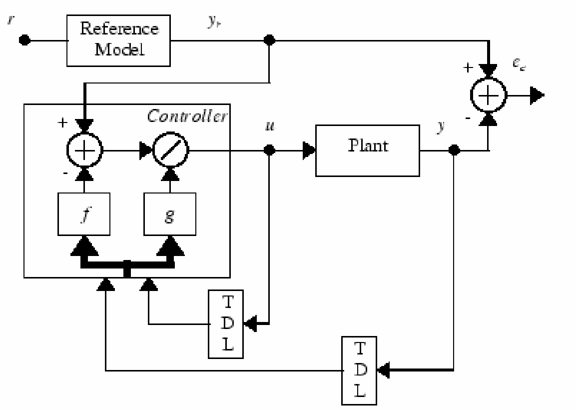

Figure 6. Operation of NARMA controller

The controller approximates the function $y_r \rightarrow u$ with a fractionally rational function of the kind (21). This function is realized with a two-layer neural network with a non-linear first layer and a linear second layer. The structure is presented in Figure 7.

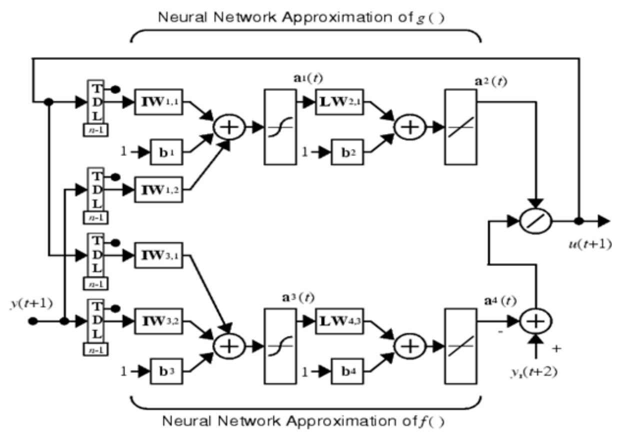

Figure 7. Structure of neural network

The training of the neural network is performed with batch training of the data. The data that trains the network are conversions of system trajectories and control signals [7], [8]. They can be submitted both currently and with various delays (TDL).

The realized function of this network is:

$$\begin{aligned} y(k+1) = f\left(y(k), y(k-1), y(k-2), ..., u(k), u(k-1), u(k-2), ...\right) + \\ + g\left(y(k), y(k-1), y(k-2), ..., u(k-1), u(k-2), u(k-3), ...\right) u(k) \end{aligned} \qquad (21)$$

where

y is the output of the object

u is the control influence of the object

f and g are approximating function in the process of the training of the neural network.

The neural model (22) is linear regarding to $u(k)$. Therefore, the reference signal $y(k+1) = \hat{y}(k+1)$, the control $u(k)$ is

$$u(k) = \frac{\hat{y}(k+1) - f\left(y(k), y(k-1), y(k-2), ..., u(k-1), u(k-2), u(k-3), ...\right)}{g\left(y(k), y(k-1), y(k-2), ..., u(k-1), u(k-2), u(k-3), ...\right)} \qquad (22).$$

5. Conclusion

In the current paper, innovative methods for control of energy flows in electric vehicles such as linearization, model predictive control and neural network control are presented. Typical structure and methods for design are proposed. Based on this research, the most effective method of the presented cannot be identified. The use of modern methods such as linearization, model predictive control and neural networks are justified in some cases, but they are implemented with more sophisticated algorithms and require more processing power, software and hardware.

Also, the classic methods with proportional-integral regulators are used when looking for lower cost and greater reliability when meeting the reference limits. The challenge for designers is to find a suitable method of a wide range, consistent with the requirements placed on the market.

Acknowledgements

The research carry out is realized in the frames of the project "Model based design of power electronic devices with guaranteed parameters", ДН07/06/15.12.2016, Bulgarian National Scientific Fund.

This research is funded in the framework of project „Gestion intelligente des flux énergétiques dans des micro- et nano-réseaux" funded by Agence Universitaire de la Francophonie and the Bulgarian National Fund for Scientific Research.

References

[1]. Ferreira Parrilla, A. (2014). *Development of energy-optimal control strategies for a fully electric vehicle* (Master's thesis).

[2]. Koca, A., Oztop, H. F., Varol, Y., & Koca, G. O. (2011). Estimation of solar radiation using artificial neural networks with different input parameters for Mediterranean region of Anatolia in Turkey. *Expert Systems with Applications*, *38*(7), 8756-8762.

[3]. Baik, I. C., Kim, K. H., & Youn, M. J. (2000). Robust nonlinear speed control of PM synchronous motor using boundary layer integral sliding mode control technique. *IEEE Transactions on Control Systems Technology*, *8*(1), 47-54.

[4]. Aliskan, I., Gulez, K., Tuna, G., Mumcu, T. V., & Altun, Y. (2013). Nonlinear speed controller supported by direct torque control algorithm and space vector modulation for induction motors in electrical vehicles. *Elektronika ir Elektrotechnika*, *19*(6), 41-46.

[5]. Rajarajeswari, N., & Thanushkodi, K. (2009). Bi-directional DC–DC converter with adaptive fuzzy logic controller. *Elektronika ir Elektrotechnika*, *89*(1), 65-68.

[6]. Kececioglu, O. F., Acikgoz, H., Gani, A., & Sekkeli, M. (2019). Experimental Investigation on Buck Converter Using Neuro–Fuzzy Controller. *International Journal of Intelligent Systems and Applications in Engineering*, *7*(1), 1-6.

[7]. Coteli, R., Acikgoz, H., Ucar, F., & Dandil, B. (2017). Design and implementation of type-2 fuzzy neural system controller for PWM rectifiers. *international journal of hydrogen energy*, *42*(32), 20759-20771.

[8]. Yu, X. H., & Li, W. (2009). Design and implementation of a neural network controller for real-time adaptive voltage regulation. *Neurocomputing*, *73*(1-3), 531-535.

[9]. Cheng, Y., Chen, K., Chan, C. C., Bouscayrol, A., & Cui, S. (2008, September). Global modeling and control strategy simulation for a hybrid electric vehicle using electrical variable transmission. In *2008 IEEE Vehicle Power and Propulsion Conference* (pp. 1-5). IEEE.

[10]. Acikgoz, H., Kale, G., Kececioglu, O. F., Gani, A., & Sekkeli, M. (2015, November). Performance analysis and design of robust controller for PWM rectifier. In *2015 9th International Conference on Electrical and Electronics Engineering (ELECO)* (pp. 1201-1206). IEEE.

[11]. Hua, G., Leu, C. S., Jiang, Y., & Lee, F. C. (1994). Novel zero-voltage-transition PWM converters. *IEEE transactions on Power Electronics*, *9*(2), 213-219.

[12]. Schaltz, E., & Soylu, S. (2011). Electrical vehicle design and modeling. *Electric vehicles-modelling and simulations*, *1*, 1-24.

[13]. Kumar, S. S., Reddy, N. R., & Rao, K. L. (2016, March). A closed loop control of three phase dual-switch buck-boost converter. In *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)* (pp. 1007-1012). IEEE.

[14]. Consoli, A., Musumeci, S., Raciti, A., & Testa, A. (1994). Sensorless vector and speed control of brushless motor drives. *IEEE Transactions on Industrial Electronics*, *41*(1), 91-96.

[15]. Moon, H. T., Kim, H. S., & Youn, M. J. (2003). A discrete-time predictive current control for PMSM. *IEEE Transactions on Power Electronics*, *18*(1), 464-472.

[16]. Le-Huy, H., Slimani, K., & Viarouge, P. (1994). Analysis and implementation of a real-time predictive current controller for permanent-magnet synchronous servo drives. *IEEE Transactions on Industrial Electronics*, *41*(1), 110-117.

[17]. French, C., & Acarnley, P. (1996). Direct torque control of permanent magnet drives. *IEEE Transactions on Industry Applications*, *32*(5), 1080-1088.

[18]. Alipour, H., Asaei, B., & Farivar, G. (2012, March). Fuzzy logic based power management strategy for plug-in hybrid electric vehicles with parallel configuration. In *Proceedings of The International Conference on Renewable Energies and Power Quality* (pp. 28-30).