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Energy Management in Microgrids Using Model Predictive Control Empowered with Artificial Intelligence

Dimitrios Trigkas[a,b,*], Georgios Gravanis[a,c], Konstantinos Diamantaras[c], Spyridon Voutetakis[a], Simira Papadopoulou[a,b]

[a]Chemical Process & Energy Resources Institute, Centre for Research and Technology Hellas (CPERI/CERTH), P.O. Box 60361, 57001 Thermi, Thessaloniki, Greece
[b]Department of Industrial Engineering and Management, International Hellenic University, 57001 Thessaloniki, Greece
[c]Department of Information and Electronic Engineering International Hellenic University, 57001 Thessaloniki, Greece
dtrigas@certh.gr

This work proposes an advanced control framework for the energy management of an islanded microgrid, using Model Predictive Control (MPC) methodology empowered with Artificial Intelligence (AI). In this hybrid approach, AI models substitute complex mathematical modelling of power assets necessary for the MPC method to operate. More specifically, Neural Network (NN) models predict the State of Charge (SOC) for each battery stack of the microgrid nodes on an hourly horizon. The predictions are then introduced to a Nonlinear MPC (NMPC) controller, substituting the process model. The efficiency of the proposed approach is compared to state of the art NMPC framework, developed for the optimal energy management of the microgrid. The simulations show that the proposed hybrid approach provides appropriate control actions for efficient energy balance in the microgrid with 6.5% average reduction of the transferred energy, compared to that of the implementation based on Mechanistic Mathematical models (MM). Indicative results are presented so as to demonstrate the capability of the proposed method to provide efficient control for optimal energy management.

1. Introduction

Efficient energy management of microgrids has gained the interest of both the scientific community and industry stakeholders. Microgrid technologies have been evolved in latest years, while several drivers and challenges such as control strategies, real-world applications and demand for efficiency have been raised (Fotopoulou et al., 2021). Several approaches have been proposed to optimize microgrid energy management (Roslan et al. 2019), targeting at efficiency measured in both economic and environmental terms, mostly using acclaimed methodologies such as Model Predictive Control (MPC), Multi-Objective Optimization, Particle Swarm Optimization and others (Mehta and Basak, 2021). Recently, Machine Learning (ML) has been introduced as a methodology either for energy management in microgrids (Wu and Wang, 2018), or for forecasting weather conditions and loads (Faraji et al. 2020). Methodologies such as Long-Short Term Memory (LSTM) are used as a predictive approach for battery SOC forecasting in NaitMalek et al. (2019) but they do not combine the predictions with an MPC methodology for the energy management. Elmouatamid et al. (2020) and Gan et al. (2021) suggest using data driven forecasting methodologies, Autoregressive Moving Average (ARIMA) and Gaussian process regression respectively, to predict several parameters such as battery charge/discharge currents. The predictions are then introduced to an MPC controller for energy management with good results. However, to the best of our knowledge, there aren't any studies comparing the efficiency between the classic MPC methodology and MPC enhanced with NNs.
Since MPC requires detailed modelling of the involved processes, that usually includes numerous complex nonlinear mathematical equations, the integration of AI into MPC methodology, provides an alternative approach to the modelling procedure based on data collected under all possible operation conditions. AI and more specific NNs can be highly adaptive depending on the problem formulation. Thus, this work proposes an architecture where state of the art NN models, are cooperating with MPC techniques for the optimal control of

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energy exchange between independent nodes of an autonomous microgrid. The mathematical prediction model of an already developed MPC controller is replaced with NN models and the operation results of the proposed architecture are compared to the developed MPC controller.

For the demonstration of the above proposed architecture, simulations of an autonomous Renewable Energy Sources (RES) oriented microgrid were conducted. This grid consists of three independent nodes with several assets for energy production and storage, such as Photovoltaics, Wind Generators, Battery Stacks, Fuel Cells, Electrolyzers and Diesel Generators. The purpose of this work is to evaluate the ability of NN models to give reliable results in the framework of MPC energy management strategy (EMS) of a microgrid and compare this framework to the classic MPC methodology, while its novelty relies on the hybrid approach where a Nonlinear MPC algorithm cooperates with NN models.

2. Preliminaries

2.1 Autonomous RES-Powered microgrid

The microgrid under consideration consists of three autonomous nodes with each of them integrating various types of energy sources (Figure 1). Photovoltaics are the main energy source in all nodes, while nodes 2 and 3 use also wind turbines. A hydrogen infrastructure is implemented additionally in node 3, where excess energy is converted to hydrogen and stored. The stored hydrogen is utilized through a fuel cell to produce energy in case of energy deficit. Each node uses a diesel generator as a backup energy source.

In normal conditions each node operates isolated from the others, satisfying the load demanded. Due to the dynamics of each node, there are differences in the amount of energy stored under isolated operation, according to simulation results (Trigkas et al., 2019). There are periods of the year that one node may have energy surplus, while the others may use the backup sources in order to compensate energy deficit.

To overcome such cases and to minimize the usage of diesel generators, the three nodes were electrically interconnected with three power converters, through a medium voltage DC bus. An NMPC controller has been developed to provide energy management in higher level. The controller targets at optimal energy exchange between the nodes in order to achieve energy balance in the network. As a result, a virtual central storage system is created (Trigkas et al., 2021) where all nodes can provide or absorb energy to satisfy the power demand while at the same time optimal RES energy exploitation is achieved and the usage of auxiliary backup energy is minimized.

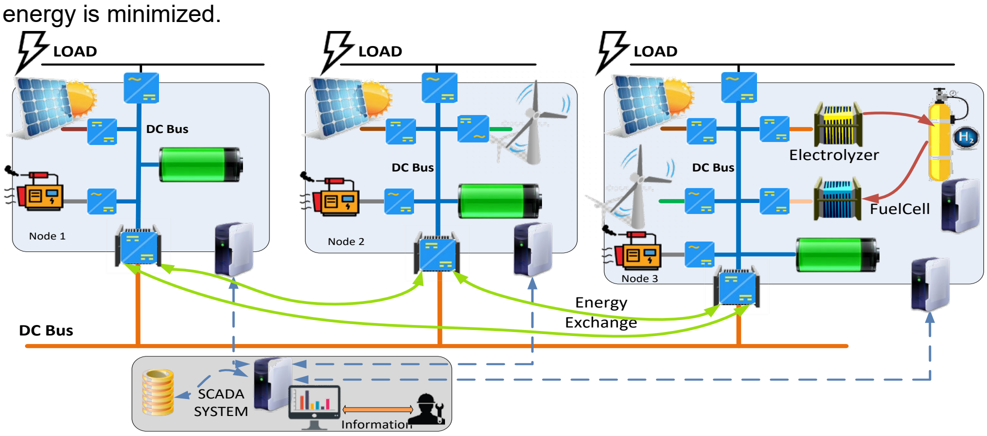

Figure 1: The topology of the multi-node microgrid

2.2 Formulation of the Non-Linear Model Predictive Control framework

The NMPC framework used in this work is proposed by Trigkas et al. (2021) and a short description is given here for the sake of paper completeness. The representation of the physical process into the mathematical formulation of the NMPC is as follows. The energy stored in the batteries is represented with the state variable vector $x(t)$, the battery state of charge (SOC) is represented by the controlled variable vector $y(t)$ and the manipulated variable vector $u(t)$ represents the power that needs to be transferred from and to each node. The optimal control problem is described by functional *J* in Eq(1) and represents a trajectory following problem, applying the minimum amount of energy.

$$J(k) = \sum_{i=1}^{m} \sum_{j=0}^{N_p-1} \left(\left(\hat{y}_i(k+j) - y_i^{sp}(k+j) \right)^T Q \left(\hat{y}_i(k+j) - y_i^{sp}(k+j) \right) + \left(u_i(k+j) \right)^T P \left(u_i(k+j) \right) \right) \quad (1)$$

The minimization of functional J provides the optimal solution for the manipulated variable $u_i(t)$ that defines the control signals to be applied on the DC/DC converter of node i in order to exchange energy with the other nodes of the microgrid. Positive values of $u_i(t)$ depict power inflow into node i and negative values depict power outflow to other nodes.

The controlled variable $\hat{y}_i(t)$ is a function of the state variable $x_i(t)$ and the manipulated variable $u_i(t)$. $y_i^{sp}(t)$ depicts the set point of the SOC of node i at time instant t. The predicted $\hat{y}_i$ for the cost function J are calculated from

$$\hat{y}_i(k+j) = y_i^{pred}(k+j) + e_i(k) \qquad j = 0, \dots, N_p - 1\,, \quad i = 1,2,3 \tag{2}$$

where

$$y_i^{pred}(\mathrm{k}+\mathrm{j}) = f_{a,i}\big(x_i(k+j), u_i(k+j)\big) \quad j = 0, \dots, N_p - 1, \quad i = 1,2,3 \tag{3}$$

is the prediction model as a function of $x_i(t)$ and $u_i(t)$, and $e_i(t)$ *is* the prediction error between the measured SOC ($y_i^{meas}(t)$) and the predicted value $y_i^{pred}(t)$ at each time instant *t*.

$$e_i(k) = y_i^{meas}(k) - y_i^{pred}(k)\,, \qquad i = 1,2,3 \tag{4}$$

In this work, the prediction horizon Tp and the control horizon Tc are both set equal to 60 min with sampling time 15 min. Therefore, there are $Np = Nc = 4$ prediction and control intervals. Matrices *Q* and *P*, are diagonal positive definite weight matrices of order N_p. Matrix *Q* defines the rate at which each node reaches the target while matrix *P* defines the significance of each node's participation in providing or receiving energy.

2.3 Time Delay Neural Networks (TDNN)

Time Delay Neural Networks have been previously used in both classification and regression applications providing good results. Gravanis et al. (2022) proposed TDNN to recognize faults in non-linear processes, while Jha and Sinha, (2014) compared TDNN and ARIMA for price forecasting with the TDNN architecture to produce better results. Figure 2 depicts the general TDNN architecture, where the size and the parameters of the feedforward neural net, depend on the problem definition. The main characteristic of the TDNN is that the memory size of the network is finite and thus can be adapted accordingly to the nature of the problem. In this study, the memory of the network is defined as m =16. With a sampling rate of 15 min the proposed model uses historical data of the previous four hours to predict the SOC of the next hour.

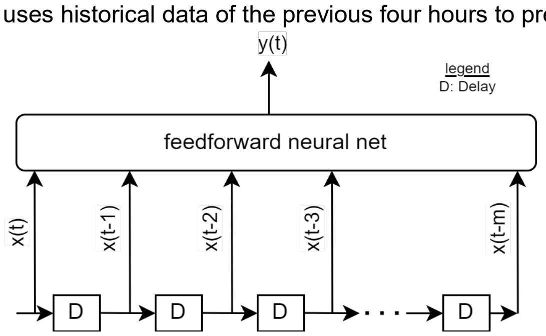

Figure 2: Time Delay Neural Network architecture

3. Forecasting methodology

3.1 Predictions with Mechanistic Mathematical models (MM)

The NMPC algorithm requires a process model to make the predictions. In the case of MM models, an analytic mathematical model of the whole structure of the microgrid was developed. The mathematical models of the devices (Photovoltaics, Wind Generators, Lead Acid Accumulators, PEM Fuel Cell, PEM Electrolyzer, Hydrogen Compressor and Hydrogen storage Tanks) were developed in MATLAB environment according to Voutetakis et al. (2011). The process model framework - Eq(3), developed from the mathematical models of the energy devices and the internal applied hierarchical EMS (Figure 3), describes the operation of each node and is used for the predictions of the NMPC algorithm (Trigkas et al. 2021). The predicted states of the batteries SOC determining the stored energy are being derived from the process models, using weather and load data. The introduced NMPC algorithm, successfully managed to optimally transfer energy between the interconnected nodes in order to balance the stored energy in the microgrid.

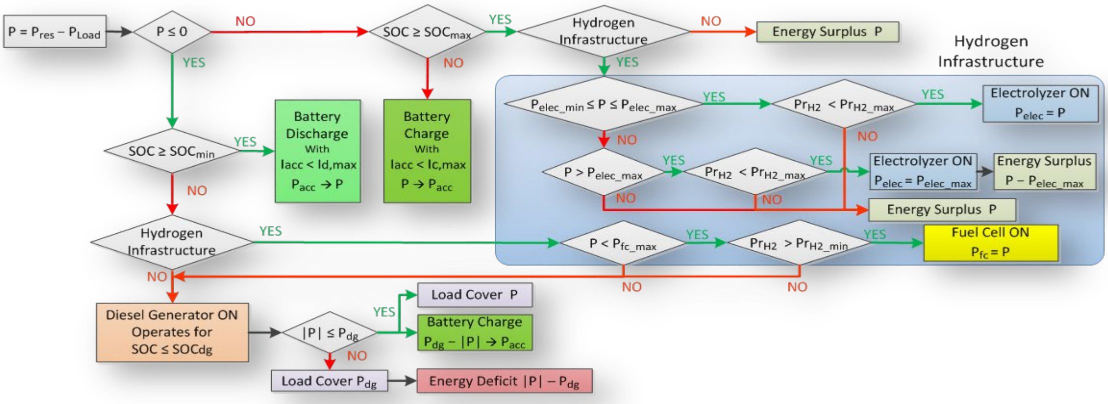

Figure 3: Internal energy management strategy algorithm at each node

3.2 Neural Networks (NN) for SOC forecasting

In the methodology described in section 3.1, the process model for the SOC prediction of each node's battery stack was developed through MM models. Developing process models based on first principals, physics and electrochemistry laws is a difficult duty and, in some cases, leads to equations of high complexity. In this paper the MM model in Eq(3), is substituted with a NN model, in order to provide a process model that can be adapted more easily to different microgrid dynamics, when data are available, and can compensate variations during process operation. To be more specific, the model used in NMPC algorithm is now derived from Time Delay Neural Networks (TDNNs) in order to predict the SOC for each battery stack. TDNN models, can capture the stochastic nature of power generation through RES, found in microgrids. Historical data of each node's battery stack was used to train models that predict the SOC value on an hourly horizon. Since different sources and constraints characterize each node, the training procedure was done with the historical data of each node separately. However, the model architecture followed for each node was identical (Table 1).

Table 1: TDNN Architecture

	Input Layer	First Hidden	Second Hidden	Output Layer	Activation Function
Nodes	16	512	256	4	RELU

The test dataset consists of 14,764 samples, that is four months with a sampling rate of 15 minutes. To capture the stochastic nature of weather, the testing set for the models consists of the middle months (January, April, July, and October) per season, while the training set consists of all the others. Figure 4 shows a four days sample of predicted and test SOC values.

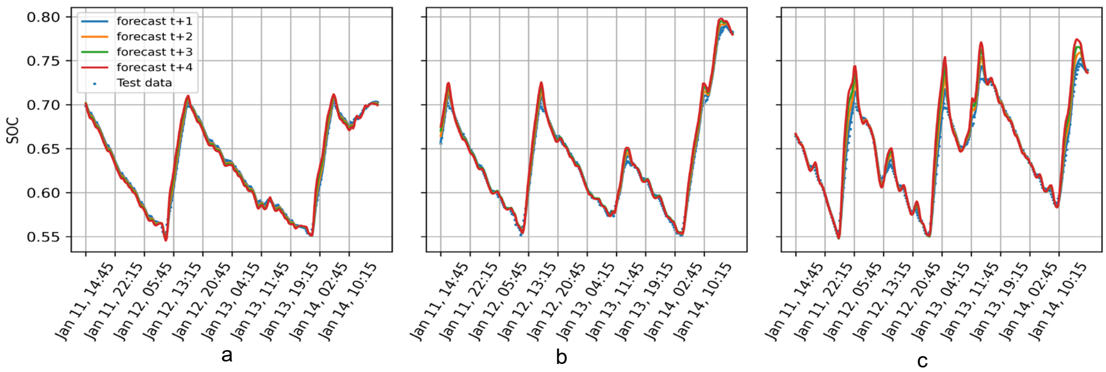

Figure 4: A sample of data indicating how SOC predictions follow the test data: a) node 1, b) node 2, c) node 3

Figure 5, depicts three scatter plots one for each node, representing the prediction accuracy of each model. The actual values are displayed on the horizontal axis, while the predicted values are on the vertical one. The figures show that the two steps ahead predictions of the SOC are quite accurate. Moreover, a minor differentiation in the accuracy is observed, as the complexity of the nodes increases (node 3 integrates a hydrogen infrastructure).

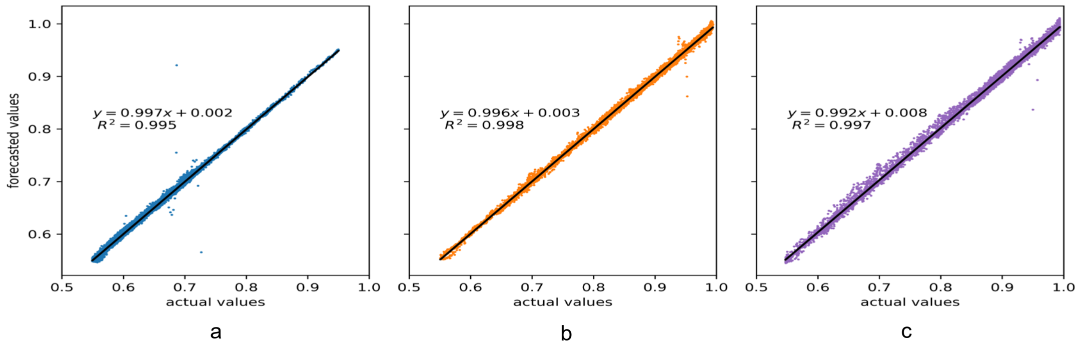

Figure 5: Predicted and test data at a horizon of 30 minutes: a) node 1, b) node 2, c) node 3

4. Operation Analysis and behavior assessment

Four pairs of simulations were carried out for months January, April, July and October, to test the effectiveness of the two methods. The operational conditions (weather and loads) of the microgrid were identical in each pair. Indicative results are shown for January (Figure 6), when the operational conditions of the microgrid are more demanding due to weather conditions. The other three pairs of simulations (April, July, and October), showed less differentiation between the two applied methods.
As Figure 6 depicts, the control actions provided by the NMPC using either MM or NN models, show similar results and in both cases the controller achieves the target of balancing the energy states among the nodes.

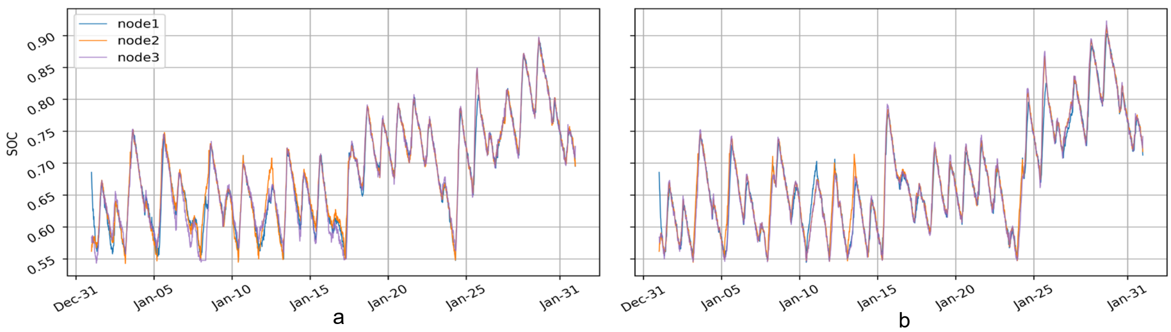

Figure 6: SOC evolution in the three nodes of the grid in January: a) with MM models and b) with NN models

Figure 7 shows the cumulative energy transfer per node throughout months January and April. The cumulative energy represents the exchanged energy balance of each node in a month period, and represents the result of the control actions provided by the NMPC. Negative values depict a total of energy export to other nodes while positive values depict energy import. Similar results with April are obtained for July and October.

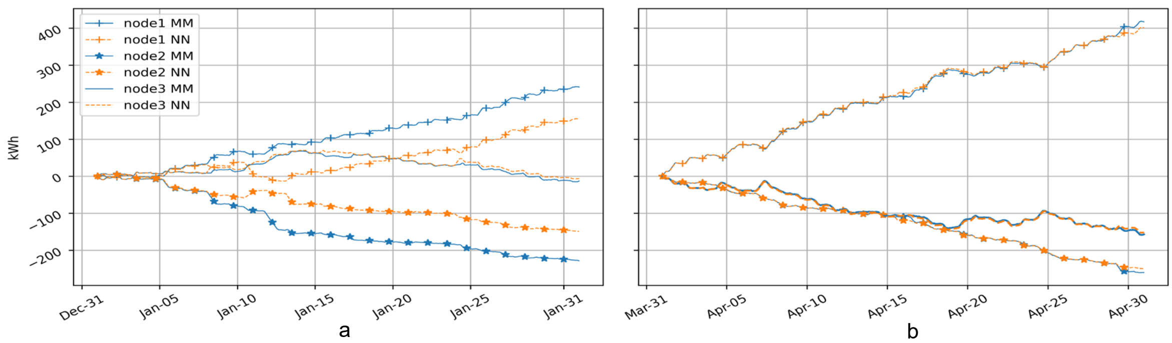

Figure 7: Cumulative energy transfer of months: a) January and b) April

Table 2 shows a comparison of the NMPC using the NN model against the MM model in terms of total energy transfer between the nodes. The usage of the NN model provides control actions that use less energy transfer to achieve the target. This is translated as lower energy cost for control implementation in the objective function in order to achieve the same target.

Table 2. Comparison of total energy transfer between nodes using the NN model against the MM model

	January	April	July	October
Energy transfer	−8.6 %	−8.53 %	−5.75 %	−2.95 %

In addition to the results presented above, it is observed that in both methods the Diesel Generators (DG) were used only in January and April. The approach with the NN model offered a more balanced DG operation among the nodes, while the total amount of energy produced did not have significant differences. Moreover, the approach is applicable for real time use since the code used in simulations, did not exceed 1.24 sec for providing the optimal control actions per step.

5. Conclusions

In this work, a hybrid approach of a NMPC controller integrating machine learning models is presented. The new hybrid approach is compared to the classic NMPC method using Mechanistic Mathematical models as the process models for predicting SOC values. The usage of NN models, in cases that sufficient and suitable amount of data are available, reduces the necessary effort of determining precise and complex mathematical models for the energy assets, subsystems and nodes of a microgrid for predicting the system's behaviour. Additionally, allows relatively easy adaptations in the system if necessary. The metric used for the evaluation of the proposed methods is the cost of energy transfer. Simulations showed that the NMPC with NN models provided control actions that required an average of 6.5% less energy transfer to achieve energy balance to the microgrid. Thus, when data are available, a hybrid approach where NN models are cooperating with NMPC can be used for the efficient energy management of microgrids.

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