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APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO ASSESS THE TREND OF ENERGY STORAGE CONTROL VARIABLES IN A MULTI-STORAGE ENERGY SYSTEM

Summary

The aim of this paper is to present the possibilities of using Artificial Neural Networks (ANNs) for the smart management of energy storage in systems with a high share of renewable energy sources. The overall method consists of two separate parts. First, optimal energy flows are simulated in EnergyPLAN, where the management of the energy system, including five energy storage systems, is optimised for daily and seasonal management. EnergyPLAN here represents an expert system from which the ANN model learns optimal energy system management. The outputs are then used in the second part which is training, validating, and testing ANNs in PyTorch for the reproduction of energy storage management with respect to the same set of input data. Input variables are related to intermittent, but predictable, supply from the wind and solar insolation, seasonal demand for grid gas, district heating demand, as well as electricity demand for BEVs. Output variables are the charge and discharge signals of all five energy storage systems, as well as the control variables of other components of the energy system. Several configurations of ANNs were tested, showing that ANNs can obtain statistically significant results, achieving an overall R2 score of 0.8 in the prediction of energy flows in all five storage systems. The results show that better performance is achieved if residual connection blocks are included in the ANN architecture and better agreement if physical constraints are integrated in the model training loss.

Key words: *Artificial Neural Network (ANN); EnergyPLAN; smart energy; energy storage; renewable energy*

1. Introduction

Energy storage and smart management have a crucial role in achieving 100% renewable energy systems (RES). Energy storage is divided by the type of energy it can balance, as well as reference balancing time. Balancing time can be short- or long-term, depending on the mismatch between renewable supply and energy demand. To find the optimal management of energy flows, *a priori* modelling is crucial. Running models with the full complexity needed to represent 100% renewable energy systems can often be optimised if a set of input variables is determined and known prior to simulation. However, the prediction of energy flows in an unknown environment requires more advanced modelling capable of learning and predicting.

The use of Artificial Neural Networks (ANNs) is known to be such a method. Research activities using ANNs as a prediction tool for energy management have resulted in a large number of proposed applications and solutions. It can be used as a forecasting tool for energy demand [1], or a forecasting load for the optimal energy management of cooling, heating, and power supply [2]. Deep learning ANNs have been used to predict a single-storage energy system with a high share of renewables and a detailed distribution network [3]. Dreher et al. demonstrated that ANNs can be employed as part of a larger algorithm for forecasting the operation of an industrial facility with the price-based control of hydrogen storage [4]. Another application of a single-storage system is presented by Qi et al. in the integration of liquid air storage, an air separation unit, and green ammonia production [5]. There are examples of using ANNs for optimising the construction of energy storage systems. Specifically, Mousavi et al. [6] examined the structural complexity of liquid air energy storage, while another study focused on the structure of a hybrid renewable energy system with hydrogen storage [7].

In the growing application of ANNs in the design and management of energy systems, the aim of this paper is to create a robust energy balance prediction system on a nationwide scale for strategic applications and to provide applicable methods for the smart management of up to 100% renewable energy systems with multiple energy storage systems. Storage systems are used for balancing highly intermittent renewable energy sources by providing power-to-vehicle, vehicle-to-grid, power-to-grid and power-to-gas processes. The paper aims to provide further insights into modelling and training techniques for applying ANNs in forecasting the behaviour of energy systems with a high share of renewables and multiple storage systems.

The novelty of the paper lies in combining the system optimisation strategies obtained with EnergyPLAN with neural networks for real-time system prediction without considering detailed features such as grid control or the dynamic behaviour of the system components. The goal is to provide a framework for integrating EnergyPLAN optimisation strategies for 100% renewable energy systems into models capable of real-time operation and scenarios where rapid predictions are needed based on changing energy supply and demand profiles.

EnergyPLAN can optimise simulations for different minimisation goals – energy imports, energy production costs, or CO_2 emissions. In the event of changes in the system structure (constraints, components, demands, electricity price, optimisation goals), EnergyPLAN simulations may be re-run, and the neural network re-trained. By running EnergyPLAN simulations with different optimisation goals, it might be possible to distil expert system knowledge, with various optimisation goals, into the ANN model which can then be used in real-time operation with optimisation goals built into the model.

2. Method - Coupling EnergyPLAN and PyTorch

In this study, the energy system is constructed in a way that consumers of energy are both in the final energy consumption sectors (transport, households and industry) and in the energy transformation sector for the production of electricity and heat. Transport sector demand consists of battery electric vehicles (BEVs) and hydrogen fuel cell electric vehicles (FCEVs). Household heat demand is divided into individual and district heating. Individual households use only heat pumps for heating, while district heating can also be supplied from gas boilers and electric heating. A detailed scheme of all features used in energy systems is presented in Fig. 3. The presented method couples the energy management tool EnergyPLAN with the PyTorch tool for the construction, training, validation, and testing of artificial neural networks. The complexity of the energy system arises from the need to integrate primary energy supply consisting entirely of intermittent renewable energy sources, namely photo voltaic (PV) and wind power, and the import of electricity. Integration is provided with the use of energy storage systems for electricity, hydrogen, thermal energy and natural gas, all having a different time of balancing (short- or long-term seasonal). The applicability of the method was assessed by comparing the predictions of the ANN models with the test data obtained from EnergyPLAN.

The overall method consists of:

1. Optimisation of energy flows through simulations of energy systems in EnergyPLAN to create datasets for ANN training;
2. Use of the PyTorch module for creating, training, and testing of ANNs for the optimal management of energy storage.

Results from the ANN validation and testing are then analysed to provide information on the structure of the neural networks and their impact on the prediction of smart storage management. The simplified view of the overall method is presented in Fig. 1.

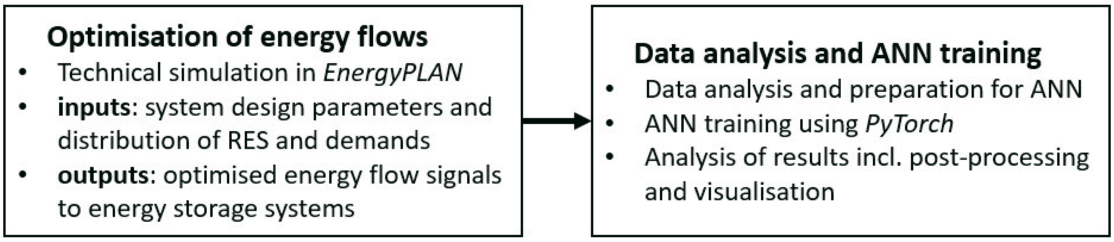

Fig. 1 Overall modelling method - from simulation of data to analysis of results

2.1 EnergyPLAN

EnergyPLAN is an energy modelling tool for the analysis of energy systems [8]. It has been widely used in research for identifying optimal transition pathways for the long-term energy planning of islands [9], for the integration of variable renewable energy sources (RES) into energy systems [10], [11], and for calculating marginal abatement cost curves, [12]. In this paper, the EnergyPLAN v16.1 was used.

EnergyPLAN explicitly emphasises whole-system balancing and sector coupling: it balances electricity, district heating/cooling, hydrogen, and grid gas hour-by-hour, with the interactions between them (power-to-heat, power-to-gas, combined heat and power (CHP) coupling, etc.) [8]. It computes non-dispatchable generation (wind/solar/run-of-river, etc.) from the hourly profiles and capacity factor and meets heat demands (households and district heating groups) with the allowed energy mix (boilers, combined heat and power, heat pumps, thermal storage). Additionally, it balances electricity by dispatching flexible units, storage, flexible demand (e.g., electric vehicle smart charging, V2G), sector-coupling converters (heat pumps and electrolysis), and finally uses energy import, export, and curtailment, depending on the strategy and the constraints. EnergyPLAN optimisation is primarily operational, and in this paper the technical simulation is used to minimise the import and export of electricity and, more generally, to find a least-fuel feasible operation within the given constraints.

EnergyPLAN has already been coupled with external tools, such as MATLAB Toolbox for improving energy planning studies for islands [13], and has been extended to the EPLANopt [14] and EPLANoptTP [15] versions. Additionally, efforts for coupling EnergyPLAN with machine learning methods have shown to speed up energy system optimisation [16]. While these frameworks deal with energy system modelling, optimisation, and analysis, in this paper optimisation strategies from EnergyPLAN simulations are used as an expert system method for training the neural network for the real-time management of energy systems.

The EnergyPLAN model setup consists of configuring the demand and supply side, as well as balancing and regulation strategies. Demand was set by hourly distributions of various sectors, such as electricity, heat, and transport. The annual values of energy must also be known. Supply was set by defining the capacities of the available supply equipment, with the exception of supply from RES, where distribution and installed capacities must be set in the model. The simulation length is one year with a time resolution of one hour to include intermittency from the renewables. Balancing and use of storage are utilised by the algorithm to reduce critical excess of electricity production, defined as the overproduction of energy within the system boundaries that exceeds export transmission capacity.

2.2 PyTorch

PyTorch is an open-source platform for training artificial neural networks using deep learning [17]. In this method, the problem is defined as time-series forecasting. The interface used to prepare and analyse the data for the ANN procedure and the post-processing of data was an in-house code written in Python [18]. The method is presented in the following block diagram:

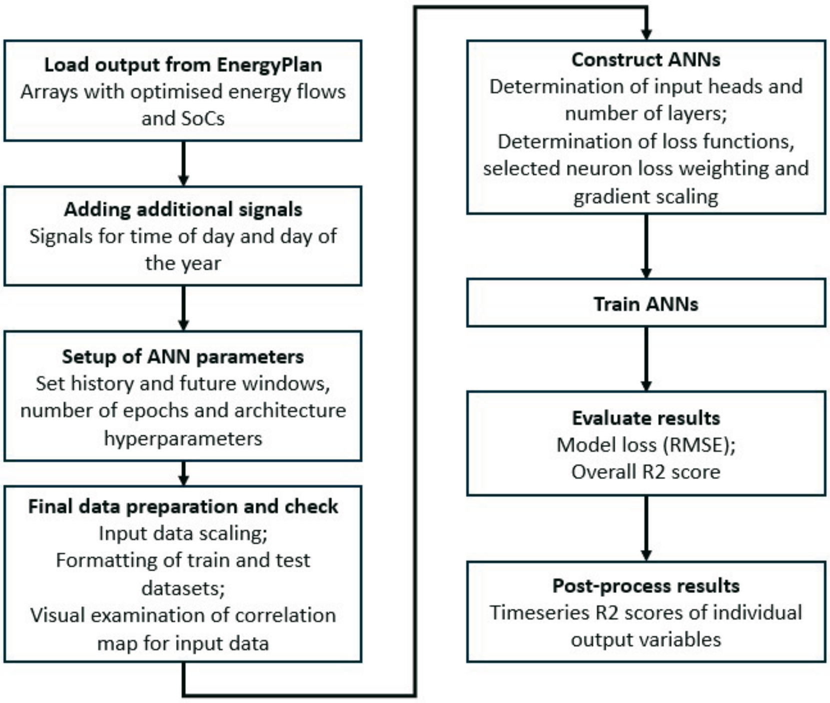

Fig. 2 Block-diagram for the ANN procedure in PyTorch. The framework consists of data loading and processing, ANN model setup, construction, training and testing, and finally result post-processing and analysis

The set of input data is an exogenous variable time series for the demand and supply of energy. Endogenous variables are presented by the state of charge (SoC) of all storage systems in the energy system. The set of output data consists of system component control variables as well as energy flow balancing signals suggesting whether storage should be charged or discharged. These signals are called action variables.

The following performance metrics of ANN training were used: the model root mean squared error (RMSE) loss and correlation parameter R2 between the test (from EnergyPLAN) and the predicted (obtained from the ANN model) set of data.

3. Hypothetical Case Study for the Energy System with a High Level of Variable Renewable Energy Sources

3.1 Design of the energy system and input data for distribution

The hypothetical energy system is presented in Fig. 3.

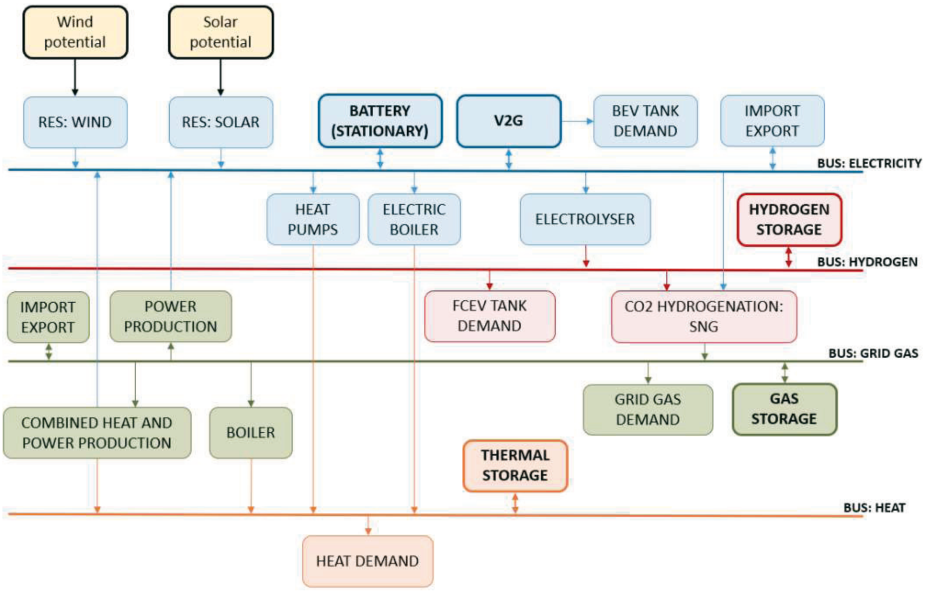

Fig. 3 Energy system for the hypothetical case study. The system includes four energy hubs (electricity, hydrogen, grid gas and heat) with components that supply, transform, and consume energy

The system consists of demand for electricity, heat, hydrogen and grid gas. The distribution for all demand is taken directly from the EnergyPLAN (distributions “IDA_Transport” for transport and “Hour_distr-heat” for grid gas). All inputs are summarised in Table 1.

Table 1 Input parameters for the hypothetical energy system

Parameter	Value	Unit	Role in the system
Electricity demand	300	GWh	demand (e)
Heat demand - individual	150	GWh	demand (q)
Heat demand – district heating	150	GWh	demand (q)
Industry demand	50	GWh	demand (gas)
Industry demand	10	GWh	demand (H_2)
Transport: H_2 (Produced by electrolysers)	34	GWh	demand (H_2)
Transport: Electricity (Dump charge)	37	GWh	demand (e)
RES: PV and wind installed capacity	750	MW	supply (e)
Transmission line capacity (import/export of electricity)	150	MW	balance (e)
Electricity storage – Charge/discharge capacities	100/100	MW	balance (e)
Electricity storage – Efficiencies	0.9/0.9	-	balance (e)
Electricity storage – Storage Capacity	0.4	GWh	balance (e)
Vehicle-to-grid (V2G) storage – Charge/discharge capacities	618/124	MW	balance (e)
Vehicle-to-grid (V2G) storage – Efficiencies	0.9/0.9	-	balance (e)
Vehicle-to-grid (V2G) storage	3.709	GWh	balance (e)
Gas storage	15	GWh	balance (gas)
Hydrogen storage	0.24	GWh	balance (H_2)
Heat storage	50	GWh	balance(q)

The amount of tank demand for transport assumes that the fleet must cover 1,027 million kilometres, having the efficiencies 3 km/kWh for FCEV and 5 km/kWh for BEV vehicles. The supply distribution for wind and PV power is taken directly from the Entso-E Transparency platform [19] for the time interval of the years 2015 – 2023 for the Republic of Croatia.

The hypothetical model presented in this paper reflects several types of time-relevant variables, meaning that there are seasonal and daily demand patterns. Grid gas demand is mainly seasonal (driven by heating demand), while hydrogen (H_2) demand for both transport and industry are constant in time. The difference between supply and demand, including intermittent wind and PV patterns, is a signal for the charge and discharge of different storage systems.

Outputs from the EnergyPLAN can be rearranged, reduced, and grouped into:

- exogenous variables:
    - Supply: wind turbines and photovoltaic (PV) power production
    - Demand:
        - electricity (general demand, transport)
        - heat (district heating, households)
        - grid gas (industry)
        - hydrogen (industry)
- action variables:
    - charge and discharge of batteries, H_2, vehicle-to-grid (V2G), thermal and grid gas storage
    - system component control variables (various components of energy production and transformation, see Fig. 3)
- endogenous variables:
    - SoC electric battery; SoC H_2 storage; SoC V2G; SoC thermal storage and SoC grid gas storage

3.2 Construction of the ANN

In this paper, two different ANN configurations are tested. They are different in terms of complexity, involving residual layer connections. The first neural network type is referred to as basic, meaning that it contains only “linear” (basic) layers, without residual connections. The design is presented in Fig. 4.

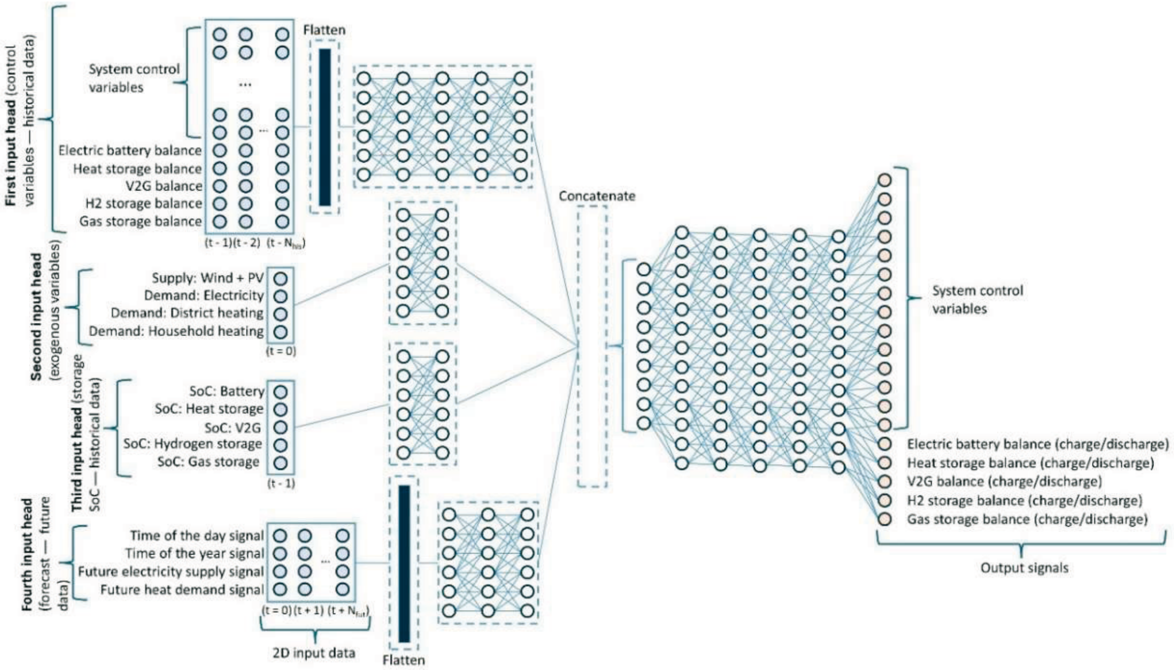

Fig. 4 Scheme of the basic network design. All network layer blocks sequentially connect into subsequent blocks

The basic model has four input heads with 5, 2, 2 and 3 "linear" layers. The input heads are concatenated together and forwarded through an additional six "linear" layers of a varying number of nodes (depending on the hidden dimension hyperparameter). Finally, the output layer has 19 nodes representing 19 output values, which are system component controls and storage balancing variables.

Since the system control variables can only have positive values as outputs, their output nodes go through an additional rectified linear unit ("ReLU") activation function. This is not the case for the balancing variables which can output both positive and negative values – representing charging and discharging of the storage. This step was taken for both basic and complex ANN models.

More complex neural networks contain residual connection blocks (as shown in Fig. 5). The assumption is that the residual connections could produce better predictions since the model only has to learn the difference in output values between time steps instead of full output values for each time step [20]. The design and residual connections are illustrated in Fig. 5.

After each "linear" layer there is also a "dropout" layer with a rate of 0.2 in the input head blocks, and 0.1 in layers after concatenation to prevent overfitting during the ANN training. Additionally, before each residual block, layer normalisation is performed to stabilise and accelerate the training process. The activation function used is a Gaussian error linear unit or "GeLU".

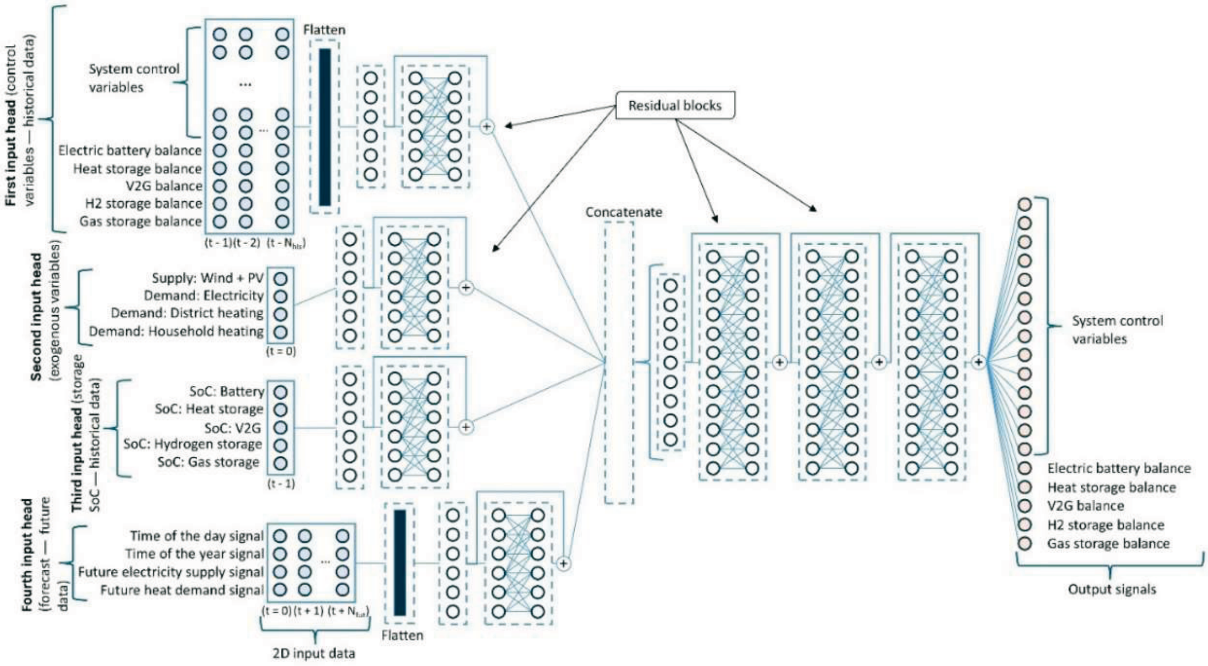

Fig. 5 Scheme of the Residual ANN model. Residual blocks contain additional informational pathways to bypass the main computational blocks

Input data are prepared for ANN training by using sliding windows to create training examples. The number of historical and future time steps, N_{his} and N_{fut}, are determined to be 24 time steps (hours) and the chosen historical and forecast signals are grouped together for every example, as shown in Fig. 6. Finally, the whole dataset is shuffled before training.

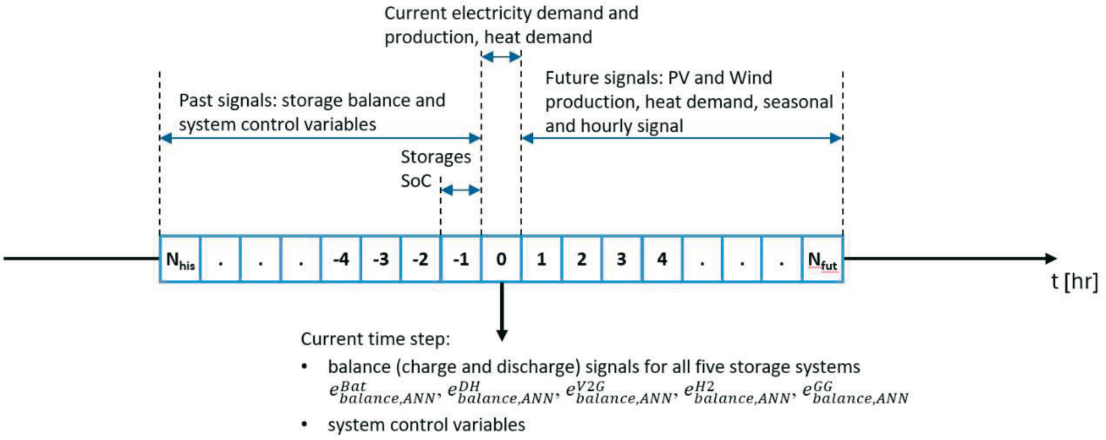

Fig. 6 Representation of input and output signals during model training and inference. Model outputs are values for storage balance and system control signals in the current time step

Input variables for both ANN models consist of the last time step (historical) values of SoCs for all five storage systems, the historical values of the system control variables, and the future signals for electricity supply and heat demand (as a proxy signal for weather forecast), as well as signals for the time of the day and the day of the year.

Furthermore, there are total of five main action variables: balance (charge and discharge) of battery, thermal storage, vehicle-to-grid (V2G), hydrogen storage, and grid gas storage: $e_{balance,ANN}^{Bat}$, $e_{balance,ANN}^{DH}$, $e_{balance,ANN}^{V2G}$, $e_{balance,ANN}^{H2}$, $e_{balance,ANN}^{GG}$.

The values of the predicted action variables are compared with the test variables from the input data: $e_{balance,T}^{Bat}$, $e_{balance,T}^{DH}$, $e_{balance,T}^{V2G}$, $e_{balance,T}^{H2}$, $e_{balance,T}^{GG}$.

3.3 Optimisation of energy flows in EnergyPLAN

Following the scheme presented in Fig. 3 with the values of the model listed in Table 1, a simulation of a nine-year period was performed by employing nine consecutive EnergyPLAN single-year simulations by taking available historical weather data as input. Fig. 7 presents the energy storage balance flows for all available years (2015–2023). The red rectangle highlights the year 2023 when ANNs would be tested, and the green rectangle highlights the validation set (year 2022). The ANN model training dataset is the EnergyPLAN results for years 2015–2021. The results for 2022 were used for hyperparameter optimisation and model validation, while the results for the final year, 2023, were used to test the final model performance.

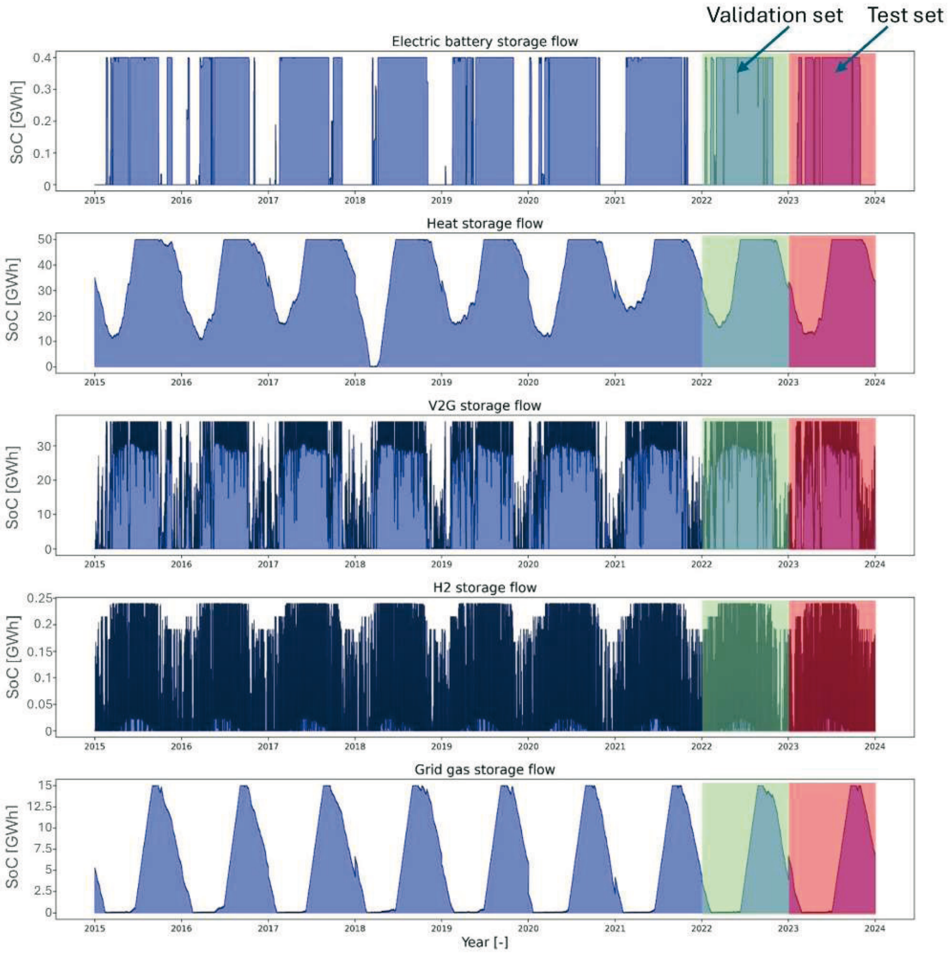

Fig. 7 EnergyPLAN results - all storage SoCs for all years modelled with highlighted years (in red) dedicated as validation and testing data. Electric battery, grid gas, and heat storage show seasonal utilisation, while V2G and H_2 storage have daily usage patterns

Grid gas, battery, and thermal storage systems have a seasonal accumulation of energy, while H_2 and V2G storage tends to balance supply and demand daily. Fig. 8 shows a cumulative histogram of charging and discharging energy flows of all energy storage systems and all years in the analysis.

Fig. 8 shows that charging and discharging patterns can be different between the years. Therefore, the constructed ANNs will have to cope with the different patterns of charging and discharging of the five storage systems.

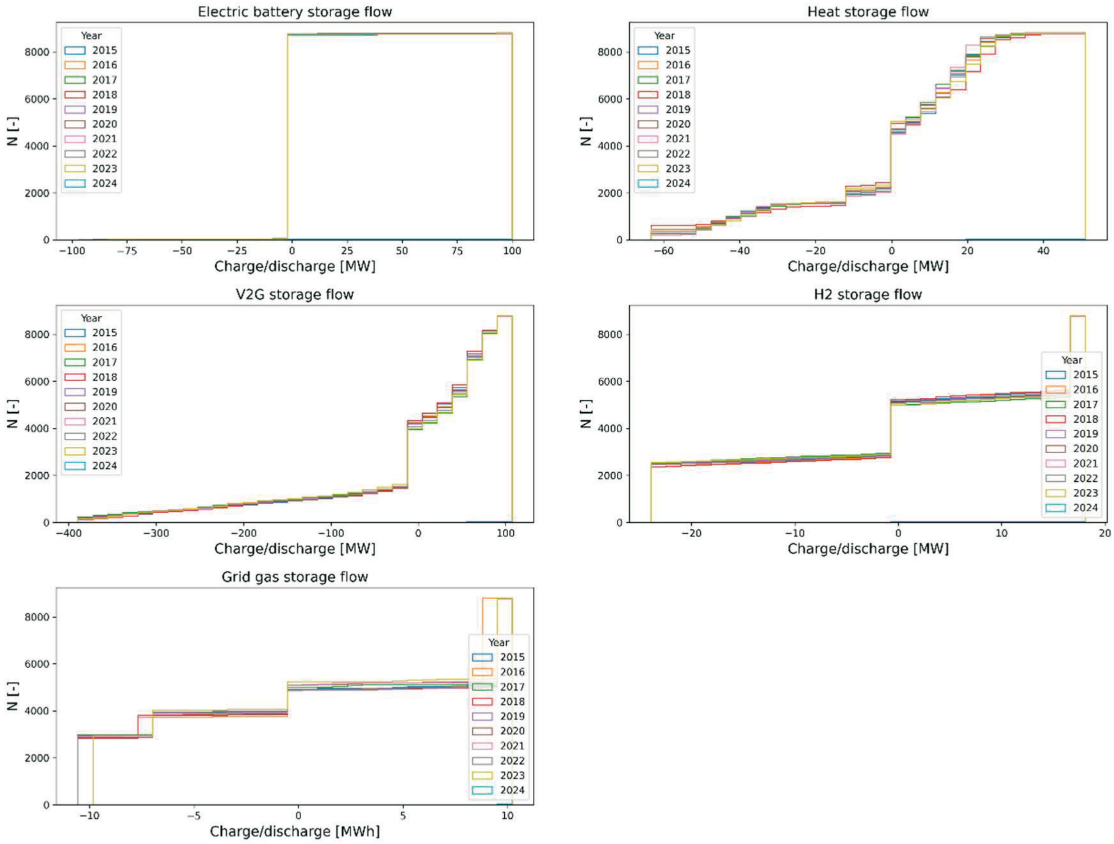

Fig. 8 EnergyPLAN results: Cumulative distribution of charging and discharging signals for all years. Although the energy flow profiles are similar between the years, they still differ based on the current state of the system and environment dynamics

Fig. 9 shows the cumulative energy flows of all components of the system for the final year of simulation.

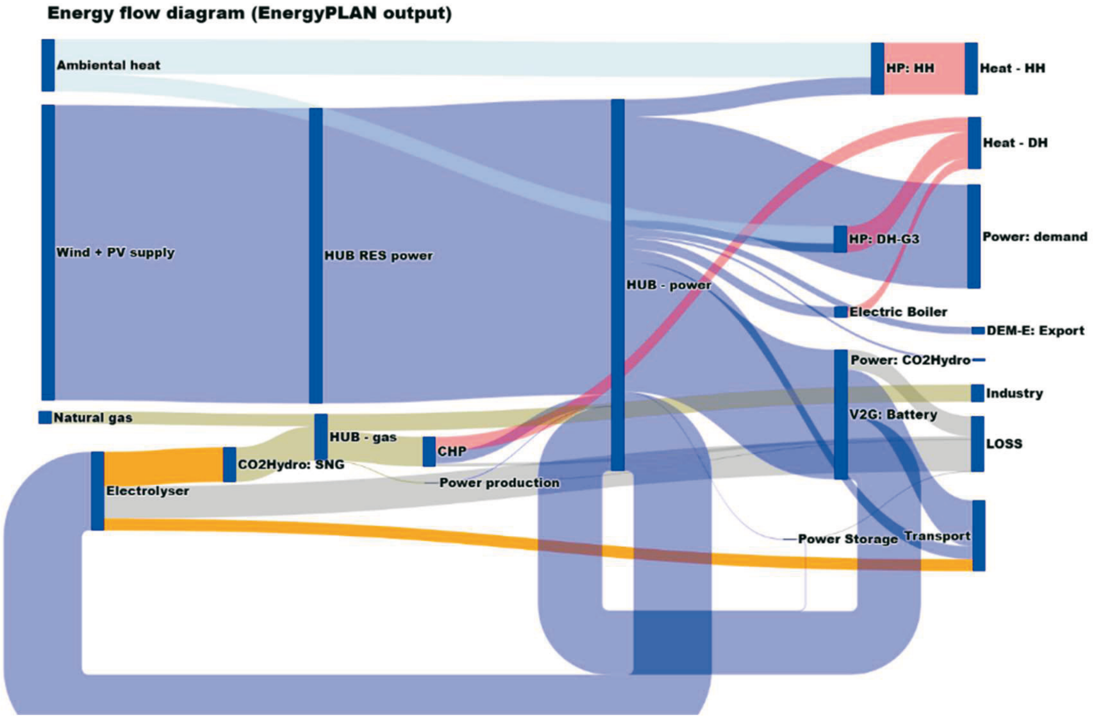

Fig. 9 EnergyPLAN results – Sankey diagram of system energy flows. Main energy sources are wind and PV energy and natural gas imports

In this paper, the results from EnergyPLAN will not be further analysed. They are taken as an input for the ANN training.

3.4 Setup of model hyperparameters and analysis of results of ANN training

3.4.1 Model training

Learning accuracy can be influenced by the choice of model hyperparameters. The main hyperparameters examined in the preliminary analysis were the size of the hidden dimensions (affecting the total number of nodes and therefore the number of learnable parameters of the model), batch size, and learning rate. The hidden dimensions varied between 512 and 2048, the learning rate between 0.0001 and 0.001, and the batch sizes from 256 to 1024.

A total of 270 cases was trained and tested as a preliminary exploration of the hyperparameters, and 12 cases were chosen for the final training and testing.

The number of epochs during the preliminary ANN training was 35, and the maximal number was 65 in the final training runs.

The best scenarios (six basic and six complex ANN models) with a description and the values of the hyperparameters are listed in Table 2.

Table 2 Setup of 12 best cases resulting from the preliminary training

Case name	ANN type	$N_{parameters}$	N_{hidden_dim}	Learning rate	Batch size
B-8-L	Basic	50 835 219	2048	0.0005	256
B-5-L	Basic	50 835 219	2048	0.0002	256
B-2-L	Basic	50 835 219	2048	0.0001	256
B-20-L	Basic	50 835 219	2048	0.0002	512
B-38-L	Basic	50 835 219	2048	0.0005	1024
R-107-S	Residual	3 633 555	512	0.0005	512
R-151-S	Residual	3 633 555	512	0.0001	1024
R-167-S	Residual	3 633 555	512	0.0002	1024
R-95-M	Residual	14 344 979	1024	0.0002	512
R-73-L	Residual	57 001 491	2048	0.001	256
R-18-S	Residual	3 633 555	512	0.0002	256

3.4.2 Model testing

Testing was done in two modes – a partial autoregressive testing mode and a full autoregressive testing mode:

- The partial mode means that the models' output signals for storage balancing are used to calculate the current SoC of the storage, which are then used as inputs in the next time step. This gives some accountability to the ANN decision signals. However, the input values for action variables are always EnergyPLAN action variable values.
- The full autoregressive testing mode is done by using all the ANN output action signals as inputs for the next time steps. This means that the model prediction errors are propagated through the next steps, as inputs, leading to lower accuracy but representing more realistic application scenarios. Because the battery balance variable consistently exhibits by far the biggest error, and the models were unable to fully learn to control the battery storage balance, this metric was also considered one of the main model performance metrics.

The results for the model loss, overall, and battery balance correlation are presented in Table 3.

Table 3 ANN results: training performance based on model RMSE loss and R2 score (in the best epochs)

Case name	Partial autoregressive testing			Full autoregressive testing		Best epoch
	Model loss [MW]	Overall R2 score [-]	Battery balance R2 score [-]	Model loss [MW]	Overall R2 score [-]	
B-8-L	5.8388	0.85545	0.27494	8.8059	0.60068	52
B-5-L	5.8586	0.83394	0.52373	6.9223	0.79297	30
B-2-L	4.4251	0.86674	0.59431	8.0872	0.66536	42
B-20-L	4.8175	0.87836	0.54046	6.7743	0.78669	44
B-38-L	6.2769	0.83468	0.41016	7.4053	0.78470	58
R-107-S	3.1311	0.95355	0.64194	6.2850	0.67297	35
R-151-S	3.6878	0.84916	0.21806	6.6035	0.76548	40
R-167-S	3.1797	0.94300	0.65078	6.5376	0.62189	45
R-95-M	**3.0725**	**0.96062**	**0.68855**	**9.0444**	**0.51834**	**55**
R-73-L	4.1775	0.84899	0.02546	8.7390	0.50285	64
R-18-S	**2.9891**	**0.95831**	**0.69534**	**7.7202**	**0.69802**	**42**

The best cases are determined as those having the highest R2 overall score. Case R-95-M has the best overall score and case R-18-S has the best battery balance control score. A few highlights emerge from the results in Table 3. ANNs with residual connection blocks (R) have on average a better R2 score than the basic cases, they converge and train faster, and require significantly fewer parameters. For complex models, an increase in ANN model size generally does not produce better results, implying that increasing the size of these models contributes to overfitting on the test data, rather than leading to useful learning and improved accuracy on test data. This is not the case for simple models, which require bigger model sizes to reach comparable levels of accuracy.

To examine the R2 score in more detail, the best cases are analysed in detail in Fig. 10.

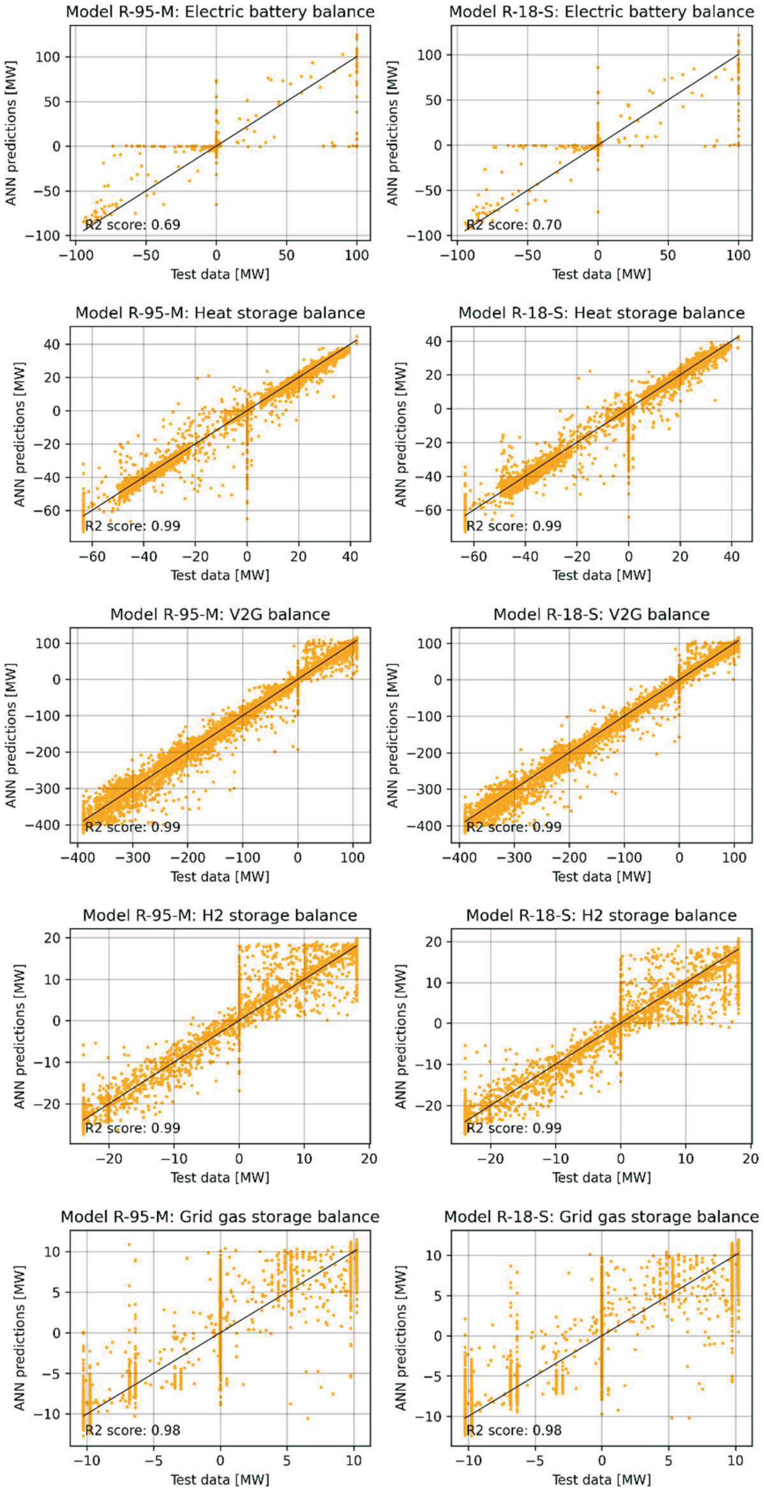

Fig. 10 Visualisation of results for best cases R-95-M and R-18-S in terms of the correlation of charging and discharging for all five storage systems (produced with partial autoregressive testing). Graphs in the first and last rows (el. battery and gas storage balances) show greater spread from the centreline, implying worse prediction capability for those storage systems.

The best R2 score shows balancing action signals (charge and discharge) of H_2, heat and V2G storage systems, and the R2 scores are similar between the charge and discharge in all storage systems, except for the electric battery.

The time series plot for energy storage for the best-case scenario model is given in Fig. 11.

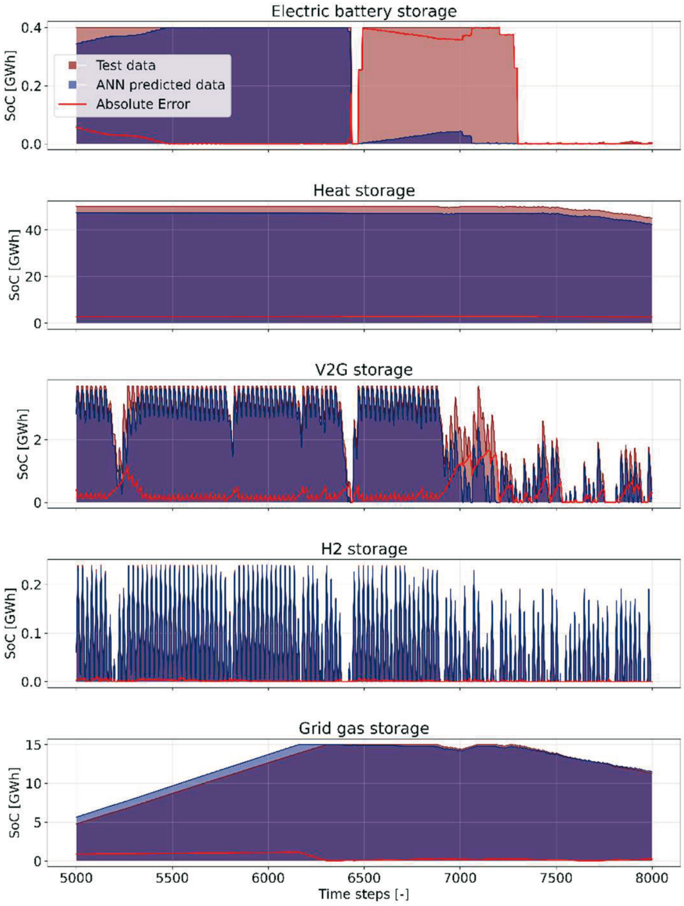

Fig. 11 ANN (partial autoregressive) test results: Timeseries of charging and discharging of all energy storage systems for case R-95-M. The red line shows the difference between the test and ANN predicted data

Fig. 11 shows the absolute error for all storage variables throughout the test sample. That was expected since the ANN performance metrics (RMSE and R2 score) were still significant.

Although the R2 score is high for all storage, except the electric battery (see Table 4), the RMSE for charging and discharging the storage is still significant. For example, in the case of V2G storage, the error is ~12MW. Although RMSEs are large in absolute values, they present only a fraction of the total capacity of the system components. For V2G, they represent about 2-9%, and for the electric battery ~4% of charge/discharge capacity.

Table 4 RMSE of storage balancing variables (and percentage difference from the ideal) for the case with the highest overall R2 score and the case for the best results for battery storage control

Case name	Battery balance	Thermal storage balance	V2G storage balance	Hydrogen storage balance	Grid gas storage balance
	RMS error [MW] (% of max.) / R2 score [-]				
R-95-M	3.74 (3.7%) / 0.689	2.77 (4%) / 0.986	12.16 (3.1%) / 0.988	1.51 (6.3%) / 0.992	1.19 (11.3%) / 0.982
R-18-S	3.69 (3.7%) / 0.695	2.76 (4%) / 0.986	11.21 (2.8%) / 0.989	1.73 (7.2%) / 0.990	1.37 (13%) / 0.977

3.5 Limitations

The main limitations of this framework are the limited training data – nine years in total, of which only seven could be used for training. The second limitation is the difference in the operational occurrence of the charging/discharging of different storage systems as a result of the EnergyPLAN simulations, for example lower battery usage (Fig. 7 and Fig. 11). The electric battery in EnergyPLAN is modelled as a pumped hydro energy storage (PHES). For this reason, it is possible for EnergyPLAN to prefer to use the V2G system component as short-term electricity storage, and the battery as mid- to long- term storage.

Fig. 12 shows some of the action variable histograms (raw EnergyPLAN output data) and R2 scores for the model output results. A connection can be seen between the value dispersion in the histogram and the R2 score. This suggests that signals which are rarely active provide a weaker training signal for the network, because the ANN model has a lower number of examples for learning dynamics and management strategy. Several methods were experimented with, such as selected neuron additional weighting (loss magnification) and gradient multiplication, but they showed no or only marginal improvement.

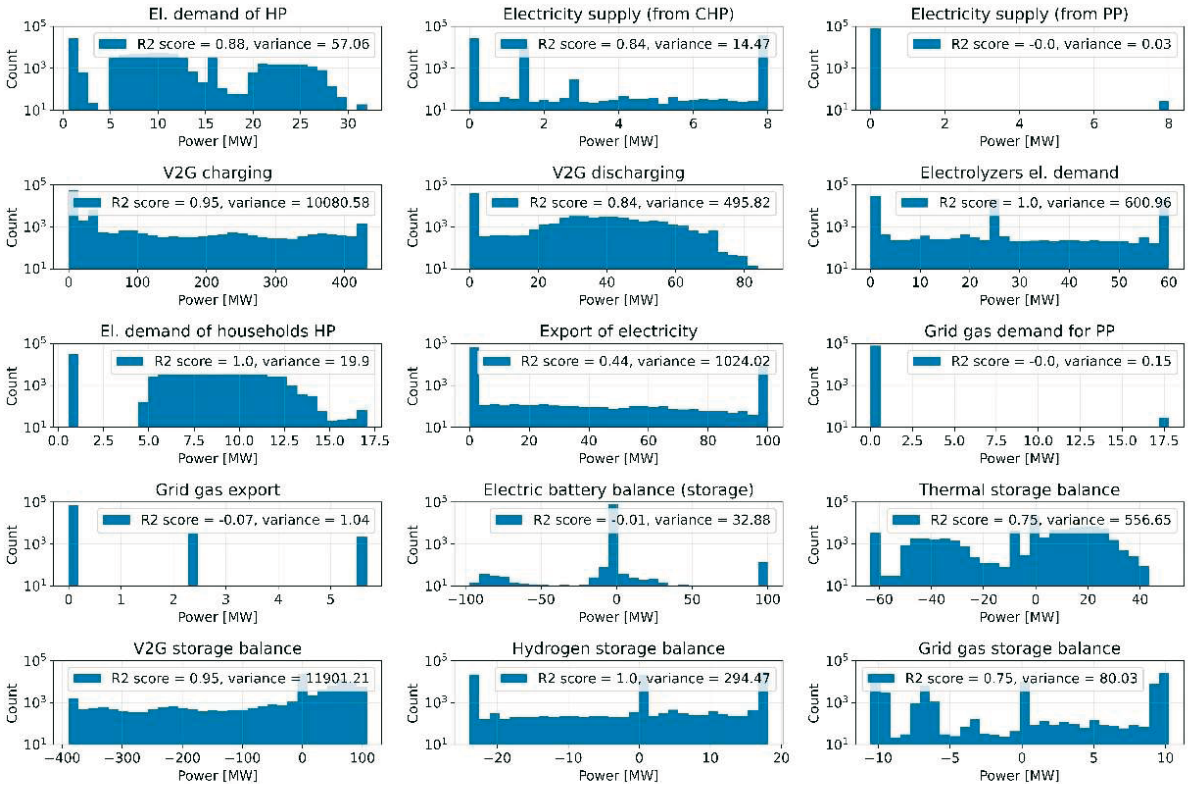

Fig. 12 Histograms of selected action variables (raw EnergyPLAN output data) and corresponding model R2 scores on test data. There is a noticeable trend of lower R2 scores for variables with low dispersion in the histogram. Data are produced with full autoregression testing.

Low battery utilisation results in low variance of the signal and likely provides poor training signals to the network. In future work, the effectiveness of various mitigation techniques must be examined (e.g. sample weighting, oversampling, etc.). Additionally, it is imperative to construct system simulation scenarios with more dynamic electric battery utilisation to ensure effective real-world operation.

Additionally, the modelling framework presented in the paper is applied to a theoretical, not a real, energy system.

3.5.1 Discussion and improvements

While the goal of training the network produces decision signals only for the next time step, the testing done in the autoregressive mode means that predictions for the current time step are used as inputs for the next steps. This leads to prediction deviations (from the ideal EnergyPLAN outputs) potentially propagating through time.

Although the R2 scores in full autoregressive testing drop substantially, the model still shows a certain level of robustness by keeping the error rate approximately constant during the full one-year testing (see Fig. 13). This shows that although the model is not perfect in following decision signals from the training data and constantly has an hourly error rate, during long-term use it still has the capacity to provide stable operation and not diverge catastrophically.

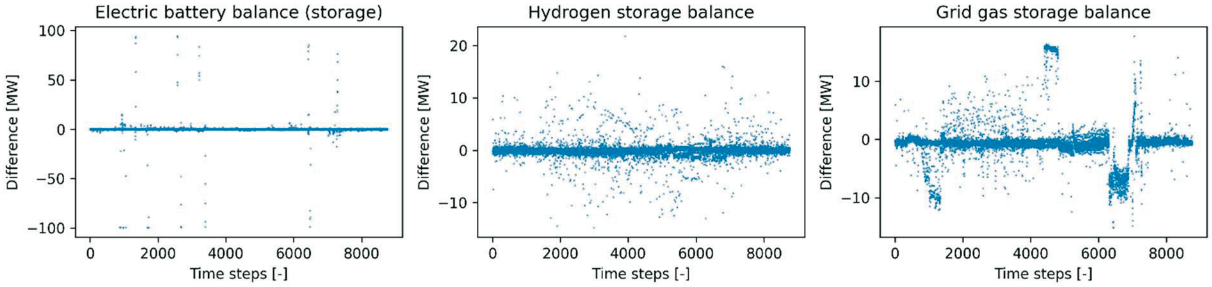

Fig. 13 Difference between the ANN predicted results and the original EnergyPLAN outputs (for the test data). Although an error is present, there is no apparent trend of growing through time (testing interval).

However, the RMSE and R2 scores might not be the proper metrics for real-world performance evaluation. Quantifying the amount of energy import (as a minimisation goal of EnergyPLAN), energy balance error (maximal and average in time) and the capability to meet electricity and heat demand could be the main criteria for real-world model performance.

For the applied operation, it is important to consider the following points:

1. In the model implementation described above, during full autoregressive testing, violation of storage charge and discharge limits and action variable capacity limits was in the order of ~2-3% on average, with violations happening ~5-10% of the time (on average), see Fig. 14.
   By constructing and applying an additional loss penalty (during training) for violation of the physical limits of particular output variables, the violation can be reduced to 1% (or less) in magnitude and occurring 1% of the time (or less), as shown in Fig. 14. With sufficient penalty weight, it is possible to a large extent to eliminate these violations. However, this comes at the expense of slower training progress and somewhat worse convergence, so implementing an optimal penalty weight is beneficial. At the rate of 1% of violations, it is likely that implementing an output value cut-off at the limit is acceptable and would not lead to large imbalances.
2. To improve the system action variables to comply with the physical constraints, auxiliary energy balance loss during training was implemented. This loss penalises the overall score based on the amount of energy hubs (electricity, thermal and grid gas) not being in balance. After determining the errors for each of the energy hubs, the absolute values of the errors are summed to provide an energy balance loss signal for the network training. Fig. 15 shows the difference between the model trained without and with the additional loss.

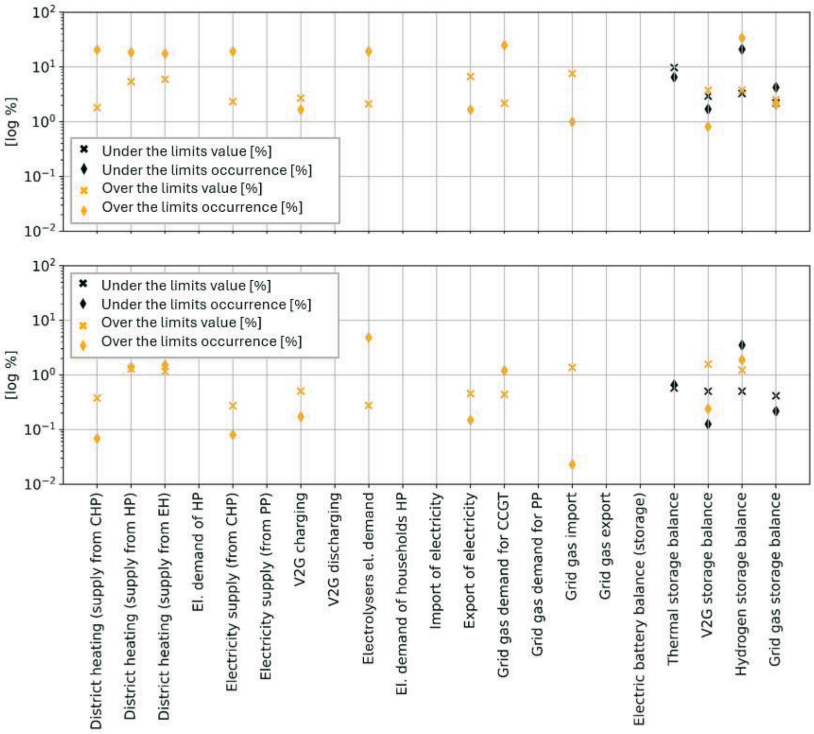

Fig. 14 Violation of physical limits of various action variables (magnitude and frequency). The upper graphic shows the results from the base model and the lower graphic displays the results from the model with an additional limit violation penalty which shows the order of magnitude reduction in violation (both in magnitude and frequency).

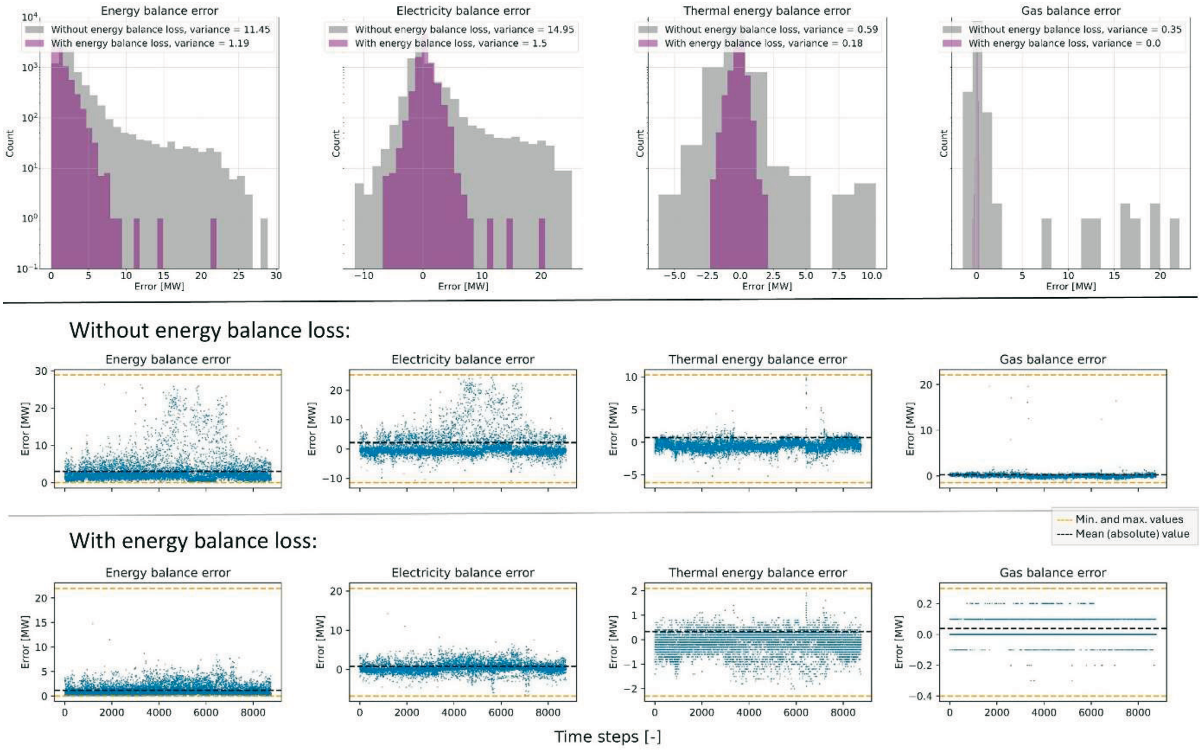

Fig. 15 Energy balance errors (difference between energy supply/production and demand/consumption). The upper row shows the histograms of errors with and without auxiliary energy balance loss. The middle row depicts the results from the base model, and the bottom row presents the results from the model with auxiliary energy balance loss. The orange lines represent minimum and maximum error values while the black line represents the average (absolute value) of the error. Errors are reduced when the energy balance loss penalty is applied (ANN model R18S with batch size 32).

The results show that by including additional energy balance loss, the electricity balance error is reduced 2.6 times (to 1.2 MW average absolute values, which is ~2% of average electricity demand), while gas and thermal balance errors improved by orders of magnitude. More importantly, peak electricity errors at specific hours are reduced by ~25% to approximately 3% of peak demand. Furthermore, in this training run, R2 scores dropped slightly (and RMSE rose slightly) when the energy balance loss is included in the training. It is difficult to draw a concrete conclusion on the influence of energy balance loss on RMSE and R2 scores since the testing results vary between training runs depending on the batch size and learning rate (even for the same architecture). Therefore, future work should further investigate the influence of energy balance loss on the training convergence for different ANN architectures and choice of hyperparameters.

3. Storage capacity saturation was not investigated, but in future work an additional loss function could be implemented to provide more constraints to the model management of storage.

4. Conclusions and future work

This paper presents a framework for using ANN for the estimation of the optimal management of energy storage in a system with a high share of renewable energy sources and with both seasonal and daily patterns of supply and demand. A dataset is obtained by running simulations in EnergyPLAN for a hypothetical energy system for the Republic of Croatia, but this framework applies to any system with an adequate corpus of input data needed for EnergyPLAN simulations. Furthermore, discussions in this paper provide more insight into combining energy system simulation frameworks with ANN models for the management of systems with a high share of renewable energy sources, energy storage, and cross-sector coupling.

The results show that with the use of ANN, energy flows can be predicted to match the test data with an overall correlation higher than 0.80, but with substantial values of absolute errors at specific hours. Models with more complex structures involving layers with residual connections showed better results. Implementing additional loss penalties for physical constraints violation (like signal physical range violation and energy balance errors) showed improvements in satisfying system constraints.

Although the method of using MLP (multi-layer perceptron model) indicates the possibility of managing energy systems by learning from expert systems, it is limited by the quality and diversity of the input data. With the implementation of additional losses, the hyperparameter space and number of design choices became even larger. Certain parameters (like batch size) show a big impact on the final results, while others have no impact or provide only marginal improvement. For this reason, to reduce absolute errors and increase the accuracy of the method, it is important to identify optimal hyperparameter values. Future work should focus on further exploring hyperparameter space and finding the optimal hyperparameters, experimenting with various architectural designs which could create richer latent representations of the system, and implementing data balancing and augmentation techniques (e.g. sample weighting, oversampling, synthetic data). Designing robust and accurate models is crucial if supervised artificial neural networks are to be used in the future as an authoritative tool for the optimal management of smart energy systems, especially if the management scenarios are highly variable.

DATA AVAILABILITY

Data and code are available from the corresponding author upon request.

COMPUTATIONAL RESOURCES

Training was done on NVIDIA GeForce RTX 4060 graphics card with 8GB of VRAM and 105W maximum power consumption. Training runs ranged from 20 to 70 mins (per run), depending on the model size, complexity, and training procedure.

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