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# ANFIS-Based Prediction of Energy Generation Influence on Electrical Demand and Price in Smart Energy Logistics

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***Abstract***

*Abstract The growing complexity of modern energy systems requires intelligent methods for managing the balance between generation, demand, and market dynamics. This paper presents an Adaptive Neuro-Fuzzy Inference System (ANFIS) model developed to predict the influence of different energy generation types on actual electrical demand and energy prices within smart energy logistics. The proposed approach integrates neuro-fuzzy reasoning to handle nonlinear relationships and uncertainty inherent in hybrid renewable systems. A comprehensive dataset covering four years of hourly electricity generation, consumption, and market prices in Spain was analyzed. Fourteen types of generation sources were considered, including fossil, hydro, nuclear, wind, and solar. The ANFIS-based model was implemented in MATLAB, using exhaustive search procedures to identify the most influential attributes for accurate forecasting. Results indicate that hydro pumped storage consumption (GHPSC) and wind onshore generation have the strongest joint impact on actual load demand, while the combination of GHPSC and fossil gas generation most significantly affects energy price variability. The findings confirm that ANFIS provides robust prediction capabilities with strong generalization and noise resistance, making it suitable for sustainable and data-driven energy management systems. The research contributes to the advancement of smart energy logistics by offering a flexible predictive framework that supports decision-making in hybrid power systems and energy market operations.*

***Keywords**: energy generation, energy logistics, electrical price, forecasting, ANFIS.*

## 1. INTRODUCTION

Demand side management of the regional integrated energy system gets increasingly challenging in the energy market as different dispersed energy sources become more prevalent. A hybrid energy system is an effective way to fulfill local electrical and thermal loads by combining several energy sources. The hybrid energy system's operator decides on optimal resource scheduling and optimal power trading with the main grid. As an unknown parameter, the price of exchanging electricity with the main grid has a significant influence on the hybrid energy system's operator's decisions.

The recent steep decline in the cost of PV panels and wind turbines provides an opportunity to utilize Hybrid Renewable Energy Systems (HRES) to fulfil thermal loads as well as the electrical demand [1]. The renewable energy resources (RESs) are naturally generated such as wind turbine, photovoltaic cell, etc. The so-called smart materials, such as piezoelectric ceramics, can also be used to induce electricity as a consequence of structural deformations [2, 3]. Those systems and elements can be used in microgrids. Demand response of the RESs has highly reduced total cost (20–30% related to the case without that) where voltage dip (maximum 1.4%) and power deviation (maximum 1.25%) are also improved in the microgrid [4]. Energy hubs (EH) are known as multi-carrier systems that integrate multiple energy resources to enable greater flexibility in the energy provision [5]. Electrical power generating cost of thermal power plant is nonlinear and non-convex in nature. Likewise, the emission produced by the thermal power plant is complex mathematical problem [6]. In this paper a concept of an integrated energy system for residential applications has been presented and by using the proposed integrated prosumer system, consumer electrical self-sufficiency may reach up to 99% (using 13 kWh battery), while covering total thermal energy demand [7]. Real-time pricing (RTP) is an effective method which can flexibly guide the supply and demand sides to adjust their behavior to participate in demand response (DR) [8]. A case study of Big Data and Machine Learning has been presented in paper [9] whose objective is to improve energy DR programs by providing accurate energy demand forecasts. The total increase of operation cost with demand response program is 5.52% less in comparison with the case no demand response program is implemented while cost deviation with demand response program is 13.28% less in comparison with no demand response program case [10]. With the penetration of intermittent renewable energy sources, greater uncertainty has been brought to the power generation system, creating increased challenges to RTP [11]. Demand-side management and load-shifting strategies can reduce peak loads as well as temporal production/consumption mismatch, two classic issues in district energy networks that integrate solar sources. Nevertheless, the classic current sizing methods for such networks only consider the total demand, and not the possible loads after use of such techniques.

The main aim in this study is to investigate which energy generation type has the strongest influence on the electrical logistics.

For electricity demand and price prediction, the adaptive neuro fuzzy inference system (ANFIS) [12] is successful in detecting and categorizing energy generating factors. ANFIS has excellent normalization and generalization capabilities, as well as noise immunity, resilience, and fault tolerance. As a consequence, changes in various energy characteristics should have little influence on the ANFIS-based electrical demand and price forecast [13, 14, 15, 16, 17, 18].

## 2 METHODOLOGY AND MATERIALS

### 2.1 Input/output data

For Spain, the information includes four years of electricity use, generation, and pricing. ENTSOE, a public platform for Transmission Service Operator (TSO) data, provided consumption and generation statistics. The Spanish TSO Red Electric provided the settlement pricing.
The dataset is unusual in that it includes hourly data on electricity use as well as TSO usage and pricing estimates. This permits future projections to be compared to the existing state of the art forecasts in use in industry. The input and output variables utilized in this investigation are listed in Table 1.

### 2.2 ANFIS methodology

The ANFIS network has five tiers, as indicated in Fig. 1. The ANFIS network's fuzzy inference technology is at its core. Layer 1 takes the inputs and converts them to fuzzy values using membership functions.
The bell-shaped membership function is used in this research because it offers the finest nonlinear data regression capabilities.

**Table 1** Input and output variables

| | Input/outputs | Min. | Max. | Std. |
|---|---|---|---|---|
| Input 1 | Generation biomass - biomass generation in MW | 333 | 580 | 51.31 |
| Input 2 | Generation fossil brown coal/lignite - coal/lignite generation in MW | 17 | 985 | 256.5107 |
| Input 3 | Generation fossil gas - coal gas generation in MW | 2990 | 9970 | 870.2561 |
| Input 4 | Generation fossil hard coal - coal generation in MW | 1820 | 8178 | 1309.655 |
| Input 5 | Generation fossil oil - oil generation in MW | 156 | 441 | 53.45646 |
| Input 6 | GHPSC – hydro1 generation in MW | 0 | 3358 | 776.7139 |
| Input 7 | Generation hydro run-of-river and poundage – hydro2 generation in MW | 429 | 1484 | 236.6572 |
| Input 8 | Generation hydro water reservoir - hydro3 generation in MW | 217 | 6427 | 1112.296 |
| Input 9 | Generation nuclear - nuclear generation in MW | 4018 | 7111 | 932.8919 |
| Input 10 | Generation other - other generation in MW | 5 | 106 | 19.83996 |
| Input 11 | Generation other renewable - other renewable generation in MW | 51 | 82 | 5.110494 |
| Input 12 | Generation solar - solar generation in MW | 16 | 5552 | 1486.772 |
| Input 13 | Generation waste - waste generation in MW | 110 | 288 | 38.93616 |
| Input 14 | Generation wind onshore - wind onshore generation in MW | 683 | 14558 | 2779.954 |
| Output 1 | Total load actual - actual electrical demand | 19500 | 39146 | 4080.66 |
| Output 2 | Price actual - price in EUR/MWh | 16.59 | 102.62 | 10.81604 |

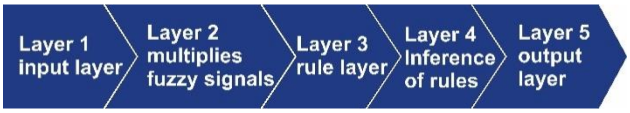


***Fig. 1** ANFIS layers*

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

where $\{a_i, b_i, c_i\}$ is the parameters set and $x$ is input. The Bell-shaped function is used for data samples fuzzyficaiton (normalization) between 0 and 1. In other words the data samples are fuzzyfied smootly based on the Bell-shaped function. Afterwards the final ANFIS results are not fuzzy but the real one.
The second layer multiplies the first layer's fuzzy signals and produces the rule's firing strength. The rule layers are the third layer, and they normalize all of the signals from the second layer. The fourht layer does rule inference and converts all signals to crisp values. The last layers summed all of the signals and provided a clean output value.
Fig. 2 shows ANFIS selection procedure in MATLAB software. ANFIS methodology was implemented for the selection procedure. During selection procedure non-relevant parameters could be removed. Parameters with small relevance do not have high impact on the output. The data set is arranged from the data file in Table 1. The dataset is partitioned into a training set (trn_data) and a checking set (chk_data). The function “exhsrch” represents exhaustive search procedure within the given inputs.

Figure 3 shows the main concept of the prediction concept through ANFIS procedure where there are two sets of input parameters. There are also two ANFIS models for each output separately. The main aim is to select optimal inputs for prediction of total load and price.

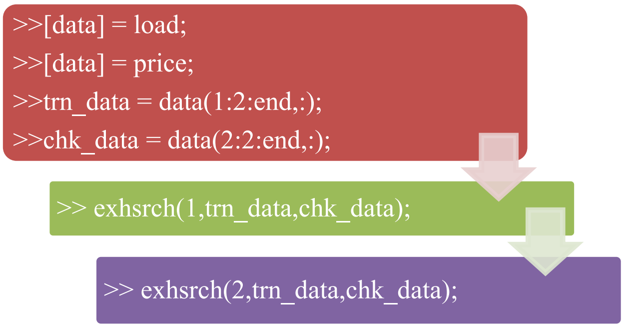


***Fig. 2*** *ANFIS selection procedure for all parameters*

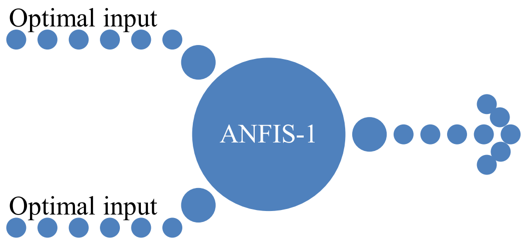


***Fig. 3*** *The main concept of the total load prediction by ANFIS procedure*

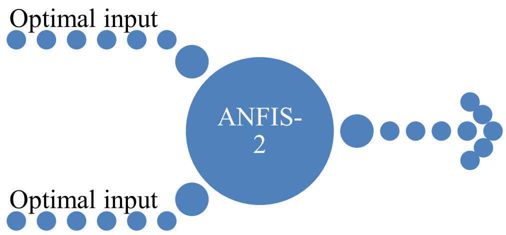


***Fig. 4*** *The main concept of the price prediction by ANFIS procedure*

## 3 RESULTS

ANFIS is used since it is soft computing technique for optimal selection of input parameters. This algorithm has fuzzy function and it-then rules hence there is soft computation where there is no need-to-know internal physical characteristics of the analyzed system. In other words, there is no need for classical analytical expressions of the data samples.

The best predictors for the different types of defects were chosen using the ANFIS approach. The selection is crucial, as is the preprocessing of the input parameters to eliminate irrelevant inputs. Following the command in MATLAB Software, the dataset is partitioned into a training set (odd-indexed samples) and a checking set (even-indexed samples):

```
>>[data] = load;
>>trn_data = data(1:2:end,:);
>>chk_data = data(2:2:end,:);

>>[data] = price;
>>trn_data = data(1:2:end,:);
>>chk_data = data(2:2:end,:);
```

The function “exhsrch” conducts an exhaustive search of the available inputs to identify the set of inputs that have the greatest impact on the actual load demand and price. The function's first parameter defines the number of input combinations that will be tested during the selection process. In essence, "exhsrch" creates an ANFIS model for each combination, trains it for one epoch, and then publishes the results. The command line below is used to find the one and two most important attributes in forecasting outputs:

```
>> exhsrch(1,trn_data,chk_data);
>> exhsrch(2,trn_data,chk_data);
```

### 3.1 Actual load demand

The impact of single input combinations on the actual load demand is shown in Fig. 5 and Table 2. RMSE training (trn) and checking (chk) mistakes are used to determine the effect. Attribute input with the smallest training error is generated by generation hydro pumped storage consumption (GHPSC), which has the greatest impact on real load demand. In other words, even little variations in the GHPSC would cause significant oscillations in the real load demand.

Based on the actual load requirement, Fig. 6 and Table 3 indicate the best combination of two input qualities. The GHPSC and Generation wind onshore combination has the least training error and hence the greatest impact on actual load demand. In other words, if GHPSC and Generation wind onshore both change at the same time, the real load demand will change the most.

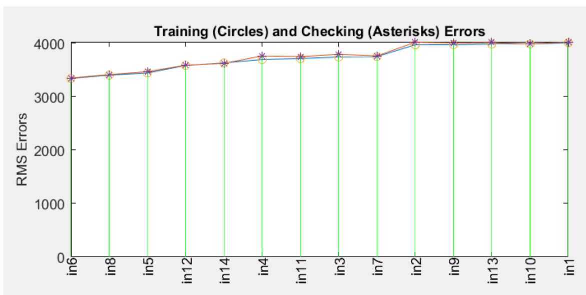


***Fig. 5*** *Correlations of one input attribute with actual load demand*

**.Table 2** Correlations of one input attribute with actual load demand

| | Input/outputs | Training | Checking |
|---|---|---|---|
| Input 1 | Generation biomass - biomass generation in MW | 4008.1828 | 4027.8546 |
| Input 2 | Generation fossil brown coal/lignite - coal/lignite generation in MW | 3971.7871 | 4019.9254 |
| Input 3 | Generation fossil gas - coal gas generation in MW | 3744.3898 | 3794.1971 |
| Input 4 | Generation fossil hard coal - coal generation in MW | 3696.3888 | 3764.2118 |

| | Input/outputs | Training | Checking |
|---|---|---|---|
| Input 5 | Generation fossil oil - oil generation in MW | 3443.7588 | 3469.3647 |
| **Input 6** | **GHPSC – hydro1 generation in MW** | **3342.1378** | **3351.1967** |
| Input 7 | Generation hydro run-of-river and poundage – hydro2 generation in MW | 3750.3922 | 3763.4841 |
| Input 8 | Generation hydro water reservoir - hydro3 generation in MW | 3404.0594 | 3412.5418 |
| Input 9 | Generation nuclear - nuclear generation in MW | 3975.2151 | 4006.9204 |
| Input 10 | Generation other - other generation in MW | 3985.7022 | 3984.4922 |
| Input 11 | Generation other renewable - other renewable generation in MW | 3713.6333 | 3749.6095 |
| Input 12 | Generation solar - solar generation in MW | 3584.6426 | 3590.0260 |
| Input 13 | Generation waste - waste generation in MW | 3985.2505 | 4012.6630 |
| Input 14 | Generation wind onshore - wind onshore generation in MW | 3632.5649 | 3623.8688 |

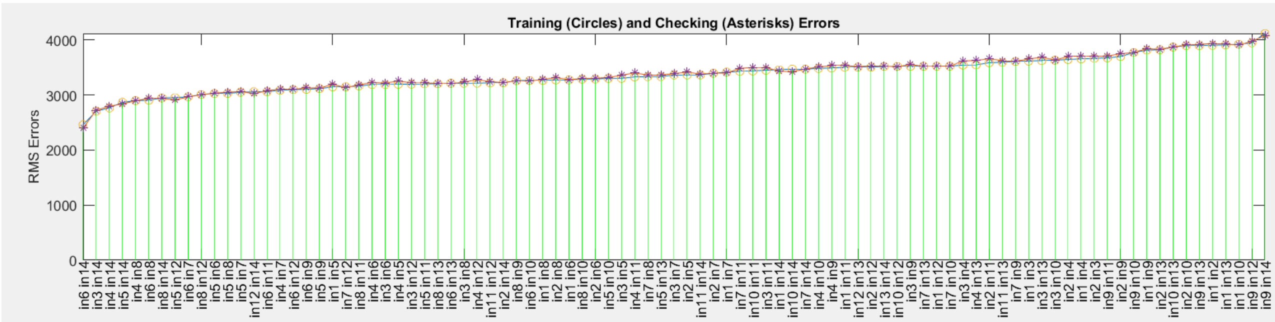


***Fig. 6*** *Correlations of two inputs attribute with actual load demand*

**Table 3** Correlations of two inputs attribute with actual load demand

| |
|---|
| ANFIS model 1: in1 in2 --> Training=3905.5810, Checking=3937.7285 |
| ANFIS model 2: in1 in3 --> Training=3619.0432, Checking=3656.1028 |
| ANFIS model 3: in1 in4 --> Training=3656.7214, Checking=3713.0967 |
| ANFIS model 4: in1 in5 --> Training=3149.3319, Checking=3194.3008 |
| ANFIS model 5: in1 in6 --> Training=3278.1786, Checking=3278.7155 |
| ANFIS model 6: in1 in7 --> Training=3417.3726, Checking=3401.4920 |
| ANFIS model 7: in1 in8 --> Training=3267.1226, Checking=3283.9556 |
| ANFIS model 8: in1 in9 --> Training=3818.3844, Checking=3843.1204 |
| ANFIS model 9: in1 in10 --> Training=3925.2842, Checking=3909.6658 |
| ANFIS model 10: in1 in11 --> Training=3507.5721, Checking=3539.9392 |
| ANFIS model 11: in1 in12 --> Training=3523.4907, Checking=3526.8796 |
| ANFIS model 12: in1 in13 --> Training=3912.8640, Checking=3927.4419 |
| ANFIS model 13: in1 in14 --> Training=3461.7435, Checking=3435.0523 |
| ANFIS model 14: in2 in3 --> Training=3668.4021, Checking=3706.4362 |
| ANFIS model 15: in2 in4 --> Training=3647.1852, Checking=3700.4389 |
| ANFIS model 16: in2 in5 --> Training=3366.7860, Checking=3418.7485 |
| ANFIS model 17: in2 in6 --> Training=3292.2950, Checking=3304.4356 |
| ANFIS model 18: in2 in7 --> Training=3396.9590, Checking=3399.3829 |
| ANFIS model 19: in2 in8 --> Training=3276.4990, Checking=3318.6157 |
| ANFIS model 20: in2 in9 --> Training=3700.1991, Checking=3750.6618 |
| ANFIS model 21: in2 in10 --> Training=3898.0606, Checking=3909.8178 |
| ANFIS model 22: in2 in11 --> Training=3589.3180, Checking=3662.1985 |
| ANFIS model 23: in2 in12 --> Training=3510.6682, Checking=3532.5164 |
| ANFIS model 24: in2 in13 --> Training=3823.2222, Checking=3831.6902 |
| ANFIS model 25: in2 in14 --> Training=3223.3965, Checking=3225.9373 |
| ANFIS model 26: in3 in4 --> Training=3545.7995, Checking=3620.4128 |
| ANFIS model 27: in3 in5 --> Training=3305.6117, Checking=3359.0515 |
| ANFIS model 28: in3 in6 --> Training=3191.7405, Checking=3218.3648 |
| ANFIS model 29: in3 in7 --> Training=3364.1012, Checking=3389.4418 |
| ANFIS model 30: in3 in8 --> Training=3215.2445, Checking=3236.7139 |
| ANFIS model 31: in3 in9 --> Training=3522.8910, Checking=3554.6512 |
| ANFIS model 32: in3 in10 --> Training=3633.6791, Checking=3637.4721 |
| ANFIS model 33: in3 in11 --> Training=3452.7363, Checking=3500.3422 |
| ANFIS model 34: in3 in12 --> Training=3199.8961, Checking=3223.5426 |
| ANFIS model 35: in3 in13 --> Training=3627.3835, Checking=3688.1488 |
| ANFIS model 36: in3 in14 --> Training=2708.9153, Checking=2724.1367 |
| ANFIS model 37: in4 in5 --> Training=3195.5280, Checking=3255.1544 |
| ANFIS model 38: in4 in6 --> Training=3191.7312, Checking=3230.9115 |
| ANFIS model 39: in4 in7 --> Training=3088.0516, Checking=3111.3622 |
| ANFIS model 40: in4 in8 --> Training=2899.8660, Checking=2898.2359 |

| |
|---|
| ANFIS model 41: in4 in9 --> Training=3491.9939, Checking=3536.4263 |
| ANFIS model 42: in4 in10 --> Training=3486.3086, Checking=3511.4179 |
| ANFIS model 43: in4 in11 --> Training=3329.7172, Checking=3405.7838 |
| ANFIS model 44: in4 in12 --> Training=3218.4846, Checking=3281.7696 |
| ANFIS model 45: in4 in13 --> Training=3549.0306, Checking=3627.5458 |
| ANFIS model 46: in4 in14 --> Training=2767.4539, Checking=2799.5368 |
| ANFIS model 47: in5 in6 --> Training=3027.8610, Checking=3034.9557 |
| ANFIS model 48: in5 in7 --> Training=3052.1170, Checking=3063.6954 |
| ANFIS model 49: in5 in8 --> Training=3031.1098, Checking=3053.1132 |
| ANFIS model 50: in5 in9 --> Training=3117.8620, Checking=3128.1453 |
| ANFIS model 51: in5 in10 --> Training=3304.7039, Checking=3321.7938 |
| ANFIS model 52: in5 in11 --> Training=3204.5559, Checking=3221.4077 |
| ANFIS model 53: in5 in12 --> Training=2952.5354, Checking=2912.4814 |
| ANFIS model 54: in5 in13 --> Training=3337.7152, Checking=3365.1002 |
| ANFIS model 55: in5 in14 --> Training=2868.2446, Checking=2838.8291 |
| ANFIS model 56: in6 in7 --> Training=2967.9815, Checking=2967.8723 |
| ANFIS model 57: in6 in8 --> Training=2907.9199, Checking=2940.0600 |
| ANFIS model 58: in6 in9 --> Training=3106.4490, Checking=3132.5671 |
| ANFIS model 59: in6 in10 --> Training=3266.9964, Checking=3256.9434 |
| ANFIS model 60: in6 in11 --> Training=3062.6094, Checking=3078.1967 |
| ANFIS model 61: in6 in12 --> Training=3099.7044, Checking=3101.0636 |
| ANFIS model 62: in6 in13 --> Training=3214.8156, Checking=3206.0898 |
| **ANFIS model 63: in6 in14 --> Training=2461.1294, Checking=2400.8804** |
| ANFIS model 64: in7 in8 --> Training=3335.8474, Checking=3361.0703 |
| ANFIS model 65: in7 in9 --> Training=3611.4123, Checking=3613.7926 |
| ANFIS model 66: in7 in10 --> Training=3525.1508, Checking=3526.6847 |
| ANFIS model 67: in7 in11 --> Training=3431.1356, Checking=3485.7254 |
| ANFIS model 68: in7 in12 --> Training=3149.8231, Checking=3137.7905 |
| ANFIS model 69: in7 in13 --> Training=3523.4171, Checking=3521.3814 |
| ANFIS model 70: in7 in14 --> Training=3472.2683, Checking=3472.7064 |
| ANFIS model 71: in8 in9 --> Training=3263.5504, Checking=3263.9678 |
| ANFIS model 72: in8 in10 --> Training=3290.6795, Checking=3302.8576 |
| ANFIS model 73: in8 in11 --> Training=3165.3290, Checking=3185.1330 |
| ANFIS model 74: in8 in12 --> Training=3011.8024, Checking=3007.9909 |
| ANFIS model 75: in8 in13 --> Training=3206.4874, Checking=3212.4550 |
| ANFIS model 76: in8 in14 --> Training=2948.5135, Checking=2939.9246 |
| ANFIS model 77: in9 in10 --> Training=3773.1920, Checking=3773.0442 |
| ANFIS model 78: in9 in11 --> Training=3676.4437, Checking=3711.1927 |

| |
|---|
| ANFIS model 79: in9 in12 --> Training=3950.9091, Checking=3978.0885 |
| ANFIS model 80: in9 in13 --> Training=3899.1366, Checking=3922.6243 |
| ANFIS model 81: in9 in14 --> Training=4119.3359, Checking=4084.0553 |
| ANFIS model 82: in10 in11 --> Training=3439.5368, Checking=3502.2770 |
| ANFIS model 83: in10 in12 --> Training=3522.0169, Checking=3515.5161 |
| ANFIS model 84: in10 in13 --> Training=3873.6744, Checking=3873.8864 |
| ANFIS model 85: in10 in14 --> Training=3472.1476, Checking=3426.0519 |
| ANFIS model 86: in11 in12 --> Training=3220.9137, Checking=3244.5920 |
| ANFIS model 87: in11 in13 --> Training=3596.8949, Checking=3623.4398 |
| ANFIS model 88: in11 in14 --> Training=3367.0390, Checking=3380.2740 |
| ANFIS model 89: in12 in13 --> Training=3508.0153, Checking=3517.2343 |
| ANFIS model 90: in12 in14 --> Training=3059.7866, Checking=3026.0081 |
| ANFIS model 91: in13 in14 --> Training=3520.7654, Checking=3526.8319 |

The ideal two-attributes are extracted and examined for future investigation. It is usually ideal to employ models with a minimal number of inputs. Fig. 7 depicts the ideal two-attribute combination for the actual load requirement.

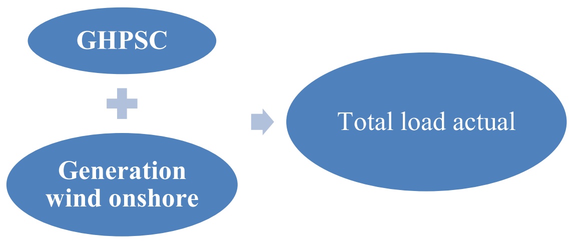


**Fig. 7** Optimal two-attributes influence on the actual load demand

Fig. 8 shows the training and checking errors for the optimal two-attributes of the actual load demand. Fig. 9 shows the ANFIS decision surface for the minimal checking error. Data distribution of the optimal two-attributes is shown in Fig. 10.

***Fig. 8** Training and checking errors for optimal two-attributes for actual load demand*

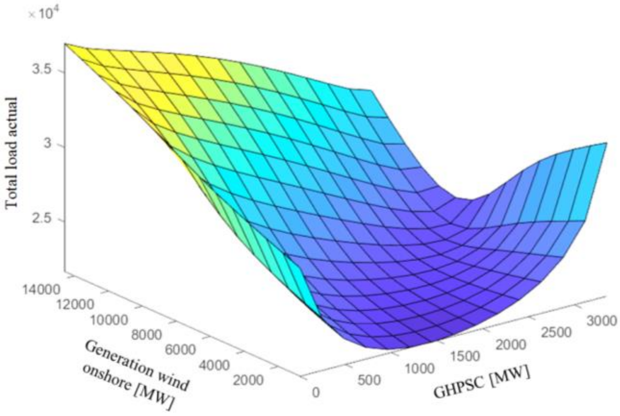


***Fig. 9** Relationship between the optimal two-attributes and the actual load demand*

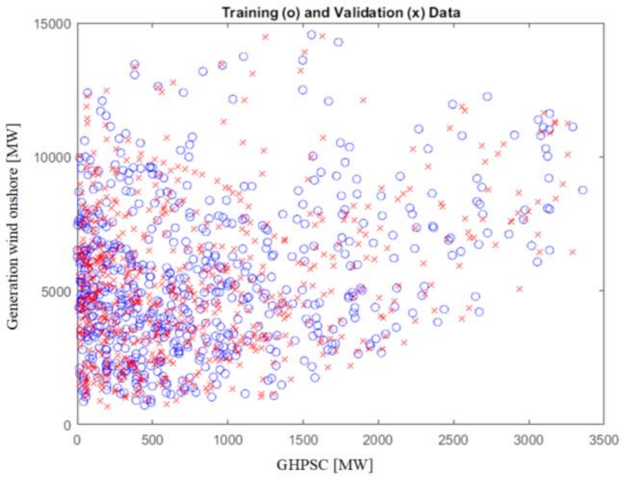


***Fig. 10** Data distribution of the optimal two-attributes for actual load demand*

## 3.2 Energy price

Fig. 11 and Table 4 shows the correlations of the influence of single input combinations on the energy price. Input attribute GHPSC has the smallest training error hence the highest influence on the energy price. In other words, any small changes of the GHPSC would provide large oscillations of the energy price.

Fig. 12 and Table 5 shows the optimal combination of two input attributes based on the energy price. Combination of Generation fossil gas and GHPSC has the smallest training error hence the highest influence on the energy price. In other words, if Generation fossil gas and GHPSC are changing in the same time it would produce the highest changing of the energy price.

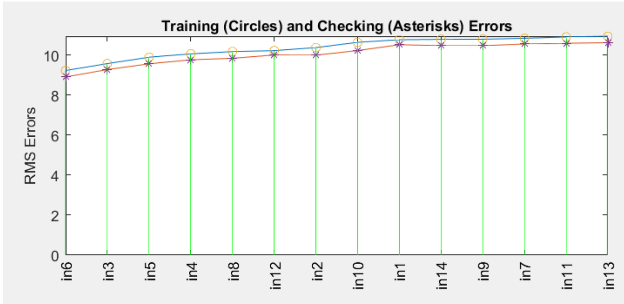


***Fig. 11** Correlations of one input attribute with energy price*

**Table 4** Correlations of one input attribute with energy price

| | Input/outputs | Training | Checking |
|---|---|---|---|
| Input 1 | Generation biomass - biomass generation in MW | 10.7767 | 10.5259 |
| Input 2 | Generation fossil brown coal/lignite - coal/lignite generation in MW | 10.3827 | 10.0052 |
| Input 3 | Generation fossil gas - coal gas generation in MW | 9.5799 | 9.2836 |
| Input 4 | Generation fossil hard coal - coal generation in MW | 10.0698 | 9.7718 |
| Input 5 | Generation fossil oil - oil generation in MW | 9.9012 | 9.5701 |
| **Input 6** | **GHPSC – hydro1 generation in MW** | **9.2343** | **8.9130** |
| Input 7 | Generation hydro run-of-river and poundage – hydro2 generation in MW | 10.8451 | 10.5619 |
| Input 8 | Generation hydro water reservoir - hydro3 generation in MW | 10.1807 | 9.8462 |
| Input 9 | Generation nuclear - nuclear generation in MW | 10.8015 | 10.4751 |
| Input 10 | Generation other - other generation in MW | 10.6460 | 10.2341 |
| Input 11 | Generation other renewable - other renewable generation in MW | 10.9140 | 10.5977 |
| Input 12 | Generation solar - solar generation in MW | 10.2286 | 10.0104 |
| Input 13 | Generation waste - waste generation in MW | 10.9509 | 10.6257 |
| Input 14 | Generation wind onshore - wind onshore generation in MW | 10.7939 | 10.4788 |

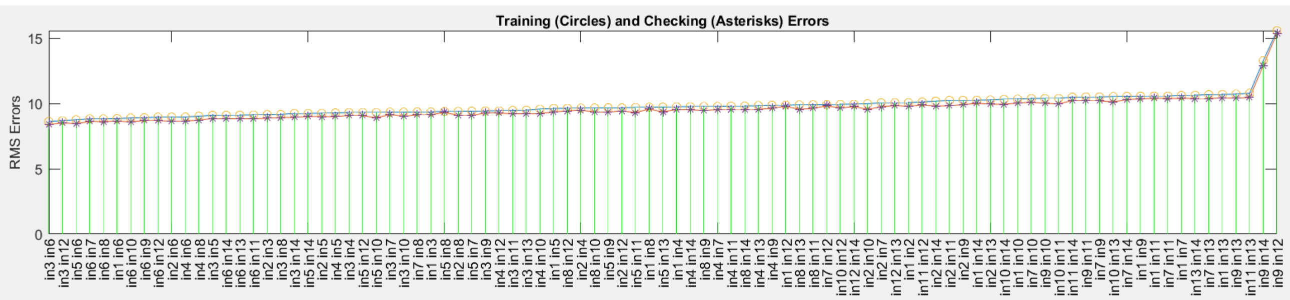


***Fig. 12** Correlations of two inputs attribute with energy price*

**Table 5** Correlations of two inputs attribute with energy price

| |
|---|
| ANFIS model 1: in1 in2 --> Training=10.0633, Checking=9.7790 |
| ANFIS model 2: in1 in3 --> Training=9.3543, Checking=9.1171 |
| ANFIS model 3: in1 in4 --> Training=9.7471, Checking=9.5362 |
| ANFIS model 4: in1 in5 --> Training=9.6192, Checking=9.3440 |
| ANFIS model 5: in1 in6 --> Training=8.8401, Checking=8.6524 |
| ANFIS model 6: in1 in7 --> Training=10.6144, Checking=10.3917 |
| ANFIS model 7: in1 in8 --> Training=9.7079, Checking=9.5636 |
| ANFIS model 8: in1 in9 --> Training=10.5559, Checking=10.3463 |
| ANFIS model 9: in1 in10 --> Training=10.3299, Checking=10.0316 |
| ANFIS model 10: in1 in11 --> Training=10.5659, Checking=10.4039 |
| ANFIS model 11: in1 in12 --> Training=9.8694, Checking=9.7843 |
| ANFIS model 12: in1 in13 --> Training=10.6925, Checking=10.4260 |
| ANFIS model 13: in1 in14 --> Training=10.2439, Checking=10.0108 |
| ANFIS model 14: in2 in3 --> Training=9.1428, Checking=8.8698 |
| ANFIS model 15: in2 in4 --> Training=9.6398, Checking=9.4828 |
| ANFIS model 16: in2 in5 --> Training=9.2428, Checking=8.9828 |
| ANFIS model 17: in2 in6 --> Training=8.9489, Checking=8.6368 |
| ANFIS model 18: in2 in7 --> Training=10.0515, Checking=9.7401 |
| ANFIS model 19: in2 in8 --> Training=9.3804, Checking=9.0725 |
| ANFIS model 20: in2 in9 --> Training=10.2427, Checking=9.9001 |
| ANFIS model 21: in2 in10 --> Training=9.9771, Checking=9.5427 |
| ANFIS model 22: in2 in11 --> Training=10.2316, Checking=9.8236 |
| ANFIS model 23: in2 in12 --> Training=9.6641, Checking=9.4244 |
| ANFIS model 24: in2 in13 --> Training=10.2648, Checking=9.9416 |
| ANFIS model 25: in2 in14 --> Training=10.1762, Checking=9.7968 |
| ANFIS model 26: in3 in4 --> Training=9.3074, Checking=9.0773 |
| ANFIS model 27: in3 in5 --> Training=9.0926, Checking=8.8523 |
| **ANFIS model 28: in3 in6 --> Training=8.6221, Checking=8.3727** |
| ANFIS model 29: in3 in7 --> Training=9.3290, Checking=9.1537 |
| ANFIS model 30: in3 in8 --> Training=9.1585, Checking=8.9248 |
| ANFIS model 31: in3 in9 --> Training=9.4228, Checking=9.2986 |
| ANFIS model 32: in3 in10 --> Training=9.3314, Checking=9.0112 |
| ANFIS model 33: in3 in11 --> Training=9.4597, Checking=9.2100 |
| ANFIS model 34: in3 in12 --> Training=8.6794, Checking=8.5174 |
| ANFIS model 35: in3 in13 --> Training=9.4880, Checking=9.2156 |
| ANFIS model 36: in3 in14 --> Training=9.2354, Checking=8.9270 |
| ANFIS model 37: in4 in5 --> Training=9.2717, Checking=8.9900 |
| ANFIS model 38: in4 in6 --> Training=8.9587, Checking=8.6647 |
| ANFIS model 39: in4 in7 --> Training=9.7611, Checking=9.5361 |
| ANFIS model 40: in4 in8 --> Training=9.0216, Checking=8.7074 |
| ANFIS model 41: in4 in9 --> Training=9.8612, Checking=9.6342 |
| ANFIS model 42: in4 in10 --> Training=9.5633, Checking=9.2259 |
| ANFIS model 43: in4 in11 --> Training=9.8011, Checking=9.5549 |
| ANFIS model 44: in4 in12 --> Training=9.4370, Checking=9.2619 |
| ANFIS model 45: in4 in13 --> Training=9.8219, Checking=9.5439 |
| ANFIS model 46: in4 in14 --> Training=9.7540, Checking=9.5219 |
| ANFIS model 47: in5 in6 --> Training=8.7483, Checking=8.4418 |
| ANFIS model 48: in5 in7 --> Training=9.4052, Checking=9.0529 |
| ANFIS model 49: in5 in8 --> Training=9.3773, Checking=9.3240 |
| ANFIS model 50: in5 in9 --> Training=9.6620, Checking=9.3347 |
| ANFIS model 51: in5 in10 --> Training=9.3125, Checking=8.9003 |
| ANFIS model 52: in5 in11 --> Training=9.6932, Checking=9.3052 |
| ANFIS model 53: in5 in12 --> Training=9.3111, Checking=9.0593 |
| ANFIS model 54: in5 in13 --> Training=9.7196, Checking=9.3463 |
| ANFIS model 55: in5 in14 --> Training=9.2375, Checking=9.0063 |
| ANFIS model 56: in6 in7 --> Training=8.8110, Checking=8.6214 |
| ANFIS model 57: in6 in8 --> Training=8.8127, Checking=8.6048 |
| ANFIS model 58: in6 in9 --> Training=8.9102, Checking=8.6976 |
| ANFIS model 59: in6 in10 --> Training=8.8822, Checking=8.5758 |
| ANFIS model 60: in6 in11 --> Training=9.1218, Checking=8.8274 |
| ANFIS model 61: in6 in12 --> Training=8.9484, Checking=8.6832 |
| ANFIS model 62: in6 in13 --> Training=9.1081, Checking=8.8386 |
| ANFIS model 63: in6 in14 --> Training=9.1006, Checking=8.8267 |
| ANFIS model 64: in7 in8 --> Training=9.3499, Checking=9.1256 |
| ANFIS model 65: in7 in9 --> Training=10.5011, Checking=10.1943 |
| ANFIS model 66: in7 in10 --> Training=10.3781, Checking=10.0884 |
| ANFIS model 67: in7 in11 --> Training=10.5712, Checking=10.3715 |
| ANFIS model 68: in7 in12 --> Training=9.9120, Checking=9.8128 |
| ANFIS model 69: in7 in13 --> Training=10.6719, Checking=10.3777 |
| ANFIS model 70: in7 in14 --> Training=10.5378, Checking=10.2964 |
| ANFIS model 71: in8 in9 --> Training=9.7587, Checking=9.4402 |
| ANFIS model 72: in8 in10 --> Training=9.6460, Checking=9.3511 |
| ANFIS model 73: in8 in11 --> Training=9.8977, Checking=9.6229 |
| ANFIS model 74: in8 in12 --> Training=9.6297, Checking=9.4276 |
| ANFIS model 75: in8 in13 --> Training=9.8922, Checking=9.5441 |
| ANFIS model 76: in8 in14 --> Training=9.8030, Checking=9.5562 |
| ANFIS model 77: in9 in10 --> Training=10.3829, Checking=10.0103 |
| ANFIS model 78: in9 in11 --> Training=10.4997, Checking=10.2137 |
| ANFIS model 79: in9 in12 --> Training=15.5724, Checking=15.3694 |
| ANFIS model 80: in9 in13 --> Training=10.7063, Checking=10.4051 |
| ANFIS model 81: in9 in14 --> Training=13.2822, Checking=12.9108 |
| ANFIS model 82: in10 in11 --> Training=10.3869, Checking=9.9610 |
| ANFIS model 83: in10 in12 --> Training=9.9337, Checking=9.6482 |
| ANFIS model 84: in10 in13 --> Training=10.5241, Checking=10.1173 |
| ANFIS model 85: in10 in14 --> Training=10.3182, Checking=9.9347 |
| ANFIS model 86: in11 in12 --> Training=10.1084, Checking=9.8812 |
| ANFIS model 87: in11 in13 --> Training=10.7804, Checking=10.4536 |
| ANFIS model 88: in11 in14 --> Training=10.4860, Checking=10.2224 |
| ANFIS model 89: in12 in13 --> Training=10.0627, Checking=9.8389 |
| ANFIS model 90: in12 in14 --> Training=9.9436, Checking=9.7611 |
| ANFIS model 91: in13 in14 --> Training=10.6291, Checking=10.3806 |

The best two-attributes are extracted and examined for further analysis. Models with a minimal number of inputs are always desirable. Fig. 13 depicts the best two-attribute combination for the energy pricing.

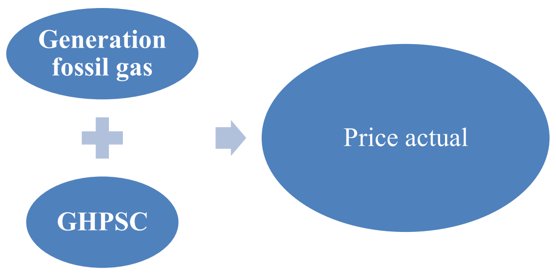


***Fig. 13*** *Optimal two-attributes influence on the energy price*

Fig. 14 shows the training and checking errors for the optimal two-attributes of the energy price. The Fig. 15 shows the ANFIS decision surface for the minimal checking error. Data distribution of the optimal two-attributes is shown in Fig. 16.

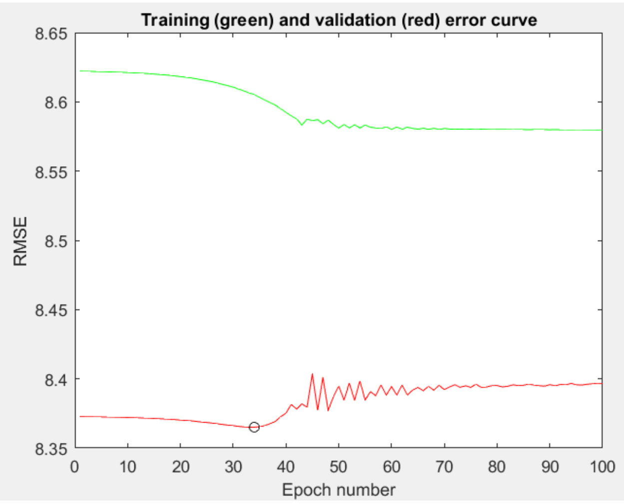


***Fig. 14*** *Training and checking errors for optimal two-attributes for energy price*

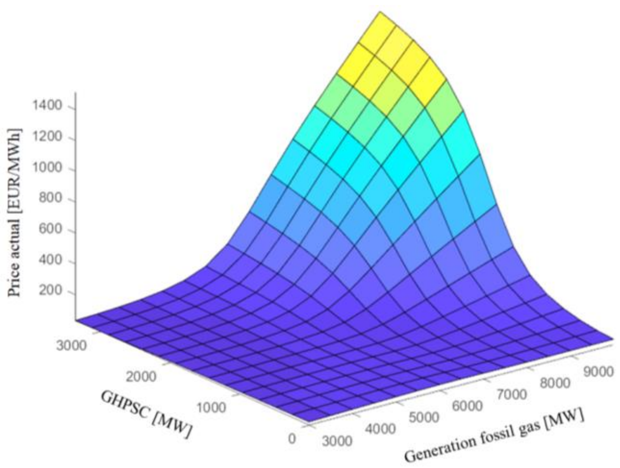


***Fig. 15*** *Relationship between the optimal two-attributes and the energy price*

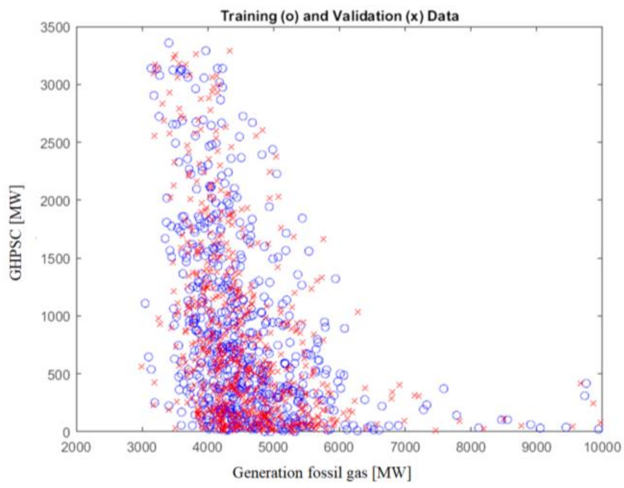


***Fig. 16*** *Data distribution of the optimal two-attributes for energy price*

## 4 CONCLUSION

Hybrid energy system is an appropriate solution to meet the local electrical and thermal loads using different energy resources. The operator of hybrid energy system decides on optimal scheduling of its resources and trading power with the main grid in an optimal way. The price of trading power with the main grid as an uncertain parameter has an important impact of the decisions of the hybrid energy system's operator.

The purpose of this research was to employ an adaptive neural fuzzy inference system (ANFIS) to classify the energy generation type for actual load demand and electrical price prediction. The simulation results show that the performance is good. ANFIS prediction shows that:

- Combination of GHPSC and Generation wind onshore has the highest influence on the actual load demand.
- Combination of Generation fossil gas and GHPSC has the highest influence on the energy price.

The study considering different energy generation type simultaneously is believed to be the first on a small scale and to attract the interest of everyone.

## REFERENCES

[1] Kahwash, F., Maheri, A., & Mahkamov, K. (2021). Integration and optimisation of high-penetration Hybrid Renewable Energy Systems for fulfilling electrical and thermal demand for off-grid communities. Energy Conversion and Management, 236, 114035.

[2] Milić, P., Marinković, D., Klinge, S., & Ćojbašić, Ž., (2023). Reissner-Mindlin Based Isogeometric Finite Element Formulation for Piezoelectric Active Laminated Shells. Tehnicki Vjesnik, vol. 30 no. 2, pp. 416-425.

[3] Milić P., Marinković D., & Ćojbašić Ž. (2025). Geometrically nonlinear analysis of piezoelectric active laminated shells by means of isogeometric FE formulation Facta Universitatis, Series: Mechanical Engineering, vol. 23, no. 2, pp. 387-405.

[4] Wang, C., Zhang, Z., Abedinia, O., & Farkoush, S. G. (2021). Modeling and analysis of a microgrid considering the uncertainty in renewable energy resources, energy storage systems and demand management in electrical retail market. Journal of Energy Storage, 33, 102111.

[5] Bidgoli, M. M., Karimi, H., Jadid, S., & Anvari-Moghaddam, A. (2021). Stochastic electrical and thermal energy management of energy hubs integrated with demand response programs and renewable energy: A prioritized multi-objective framework. Electric Power Systems Research, 196, 107183.

[6] Jebaseelan, S. S., Selvan, N. M., Kumar, C., Kalaimurugan, A., Srujana, A., & Ravi, C. N. (2021). Solving constrained economic electrical energy generation and CO2 emission dispatch using hybrid algorithm. Environmental Technology & Innovation, 101999.

[7] Kotowicz, J., & Uchman, W. (2021). Analysis of the integrated energy system in residential scale: Photovoltaics, micro-cogeneration and electrical energy storage. Energy, 227, 120469.

[8] Yuan, G., Gao, Y., & Ye, B. (2021). Optimal dispatching strategy and real-time pricing for multi-regional integrated energy systems based on demand response. Renewable Energy, 179, 1424-1446.

[9] Gómez-Omella, M., Esnaola-Gonzalez, I., Ferreiro, S., & Sierra, B. (2021). k-Nearest patterns for electrical demand forecasting in residential and small commercial buildings. Energy and Buildings, 253, 111396.

[10] Taghizadeh, M., Bahramara, S., Adabi, F., & Nojavan, S. (2020). Optimal thermal and electrical operation of the hybrid energy system using interval optimization approach. Applied Thermal Engineering, 169, 114993.

[11] Zhang, L., Gao, Y., Zhu, H., & Tao, L. (2022). Bi-level stochastic real-time pricing model in multi-energy generation system: A reinforcement learning approach. Energy, 239, 121926.

[12] Jang, J.-S.R, ANFIS: Adaptive-Network-based Fuzzy Inference Systems, IEEE Trans. On Systems, Man, and Cybernetics (1993), Vol.23, 665-685.

[13] I. Mladenović, D. Marković, M. Milovančević, and M. Nikolić, “Extreme learning approach with wavelet transform function for forecasting wind turbine wake effect to improve wind farm efficiency,” Advances in Engineering Software, vol. 96, pp. 91–95, 2016, doi: 10.1016/ j.advengsoft.2016.02.011.

[14] V. Nikolić, J. Kaljević, S. Jović, D. Petković, M. Milovančević, L. Dimitrov, and P. Dachkinov, “Survey of quality models of e-learning systems,” Physica A: Statistical Mechanics and its Applications, vol. 511, pp. 324–330, 2018, doi: 10.1016/j.physa.2018.07.058.

[15] B. Novković-Cvetković, M. Gligorijević, D. Petković, S. Jović, M. Milovančević, and V. Nikolić, “Evaluation of information and communication technology sector in the teaching process and strategic collaboration between universities and industry,” Computer Applications in Engineering Education, vol. 27, no. 3, pp. 653–662, 2019, doi: 10.1002/cae.22105.

[16] H. Deneva, E. Teirumenieka, L. Lazov, V. Nikolić, and M. Milovančević, “Analysis of the influence of auxiliary gas pressure on cut characteristics of laser cut steel,” Lasers in Engineering, vol. 40, no. 4–6, pp. 253–263, 2017, doi: 10.1016/j.infrared.2018.04.007.

[17] B. Jokanović, B. Lalić, M. Milovančević, N. Simeunović, and D. Marković, “Economic development evaluation based on science and patents,” Physica A: Statistical Mechanics and its Applications, vol. 481, pp. 141–145, 2017, doi: 10.1016/j.physa.2017.04.015.

[18] V. Nikolić, M. Milovančević, D. Petković, D. Jocić, and M. Savić, “Parameters forecasting of laser welding by the artificial intelligence techniques,” Facta Universitatis, Series: Mecha–nical Engineering, vol. 16, no. 2, pp. 193–201, 2018, doi: 10.22190/FUME180526025N.

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