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Optimum design of distributed energy hubs using hybrid surrogate models (HSM)

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Abstract

The energy hub concept is gradually getting popular due to its capability to integrate renewable energy technologies into the energy grid with a minimum impact. Designing distributed energy hubs is a challenging task due to the coupling of optimum dispatch and energy system sizing problems. Operation of the system needs to be considered for 8760 time steps and energy system sizing optimization can take several days to complete. This time must be shortened in order to make it easier to optimize the multi-energy hubs connected to multi energy grids where there is a strong coupling among energy hubs and network. This study introduces a novel optimization algorithm, coupling an existing energy hub model with a hybrid surrogate model in order to reduce computational time in the optimization process.

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Keywords: Distributed energy systems; electrical hub; surrogate models; multi-objective optimization

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1. Introduction

Distributed energy systems can play a vital role when integrating SPV and wind energy technologies [1]. A number of different concepts such as virtual plants, smart micro-grids, energy hubs, integrated energy systems etc. are emerging within the umbrella of distributed energy systems due to their potential to integrate non-dispatchable energy technologies into the grid with a minimum impact [2]. Distributed energy systems consist of different system components such as solar PV (SPV) panels, wind turbines, energy storage devices (such as battery banks, H2 fuel cells etc.) and dispatchable energy sources (such as internal combustion generators, gas turbines etc.), which are complementary to each other. Therefore, a number of options can be considered when operating an energy system [3]. As a result, both dispatch and energy system sizing problems have to be considered simultaneously when designing distributed energy systems which make it a challenging task. Furthermore, higher computational time is taken for the optimization process, which can take from a few days up to a week [4]. Hence, it is important to look for promising methods that can reduce the computational time when designing distributed energy systems. In order to address this research problem, a novel computational algorithm with the assistance of a surrogate model is introduced in this study. A brief overview about the energy hub concept is presented in Section 2. Section 3 of this article presents an overview of the computational algorithm proposed to combine the surrogate model with the Actual Engineering Model (AEM). Section 5 and 6 present the actual engineering model used and the surrogate model developed. Finally, the results obtained from the analysis are presented in Section 7.

2. Overview of the Energy hub

Direct integration of non-dispatchable energy technologies such as SPV panels and wind turbines is challenging due to the fluctuations in demand and generation. The energy hub is getting gradually popular as a method to integrate non-dispatchable renewable energy technologies into the grid. Energy hubs combine dispatchable energy sources and energy storage along with non dispatchable energy storage which helps to absorb the fluctuations. A simple energy hub consisting of wind turbines, SPV panels, battery bank and ICG operating connected to the grid is considered in this study (Fig. 1). The energy hub is maintaining interactions with the grid in both forms of purchasing and selling electricity. Grid curtailments are introduced for both selling and purchasing electricity considering the stability of the grid. Time of use (TOU) pricing scheme is considered in this study when determining the price of electricity in the grid.

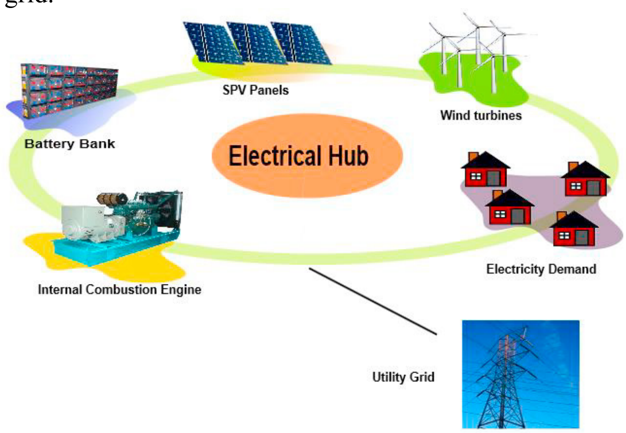

Fig.1 Overview of the energy hub

3. Overview of the computational model

Surrogate models are black box models that simply present the relationship between input and output, bypassing a complex computational model which takes considerable computational time. Although surrogate models are fast in computation, these models cannot completely replace actual engineering models (AEM) in most of the instances.

Hence, surrogate models should be combined with AEM in order to reach the optimum design solution using less computational time. Black box models such as neural networks, support vector machines etc. (as described in Section 4) are used to map decision space variables into objective space in surrogate models, which is a single step process when compared to AEM (Fig. 2). AEM is more accurate when computing the objective function. However, it takes considerable computational time to compute the objective function values when compared to surrogate models. On the other hand, surrogate models are much faster in computing but lack in accuracy. Hence, there should be an optimum combination of surrogate models and AEMs to obtain the Pareto set. In this study, we try to combine surrogate models sequentially with AEM and we name this method Sequential Surrogate Model (SEM).

SEM consists of two steps: 1) a surrogate model is initially used with the optimization algorithm to generate the initial Pareto front, 2) the initial Pareto front is used as the starting point for the secondary stage optimization which is using AEM. Higher computational speed of the surrogate model helps the optimization algorithm to reach to the Pareto front faster. However, AEM is used in the second stage which maps decision space variables into the objective space with a better accuracy. Therefore, the surrogate model in SEM helps reaching the actual Pareto front within a short period of time, which is later refined using the AEM.

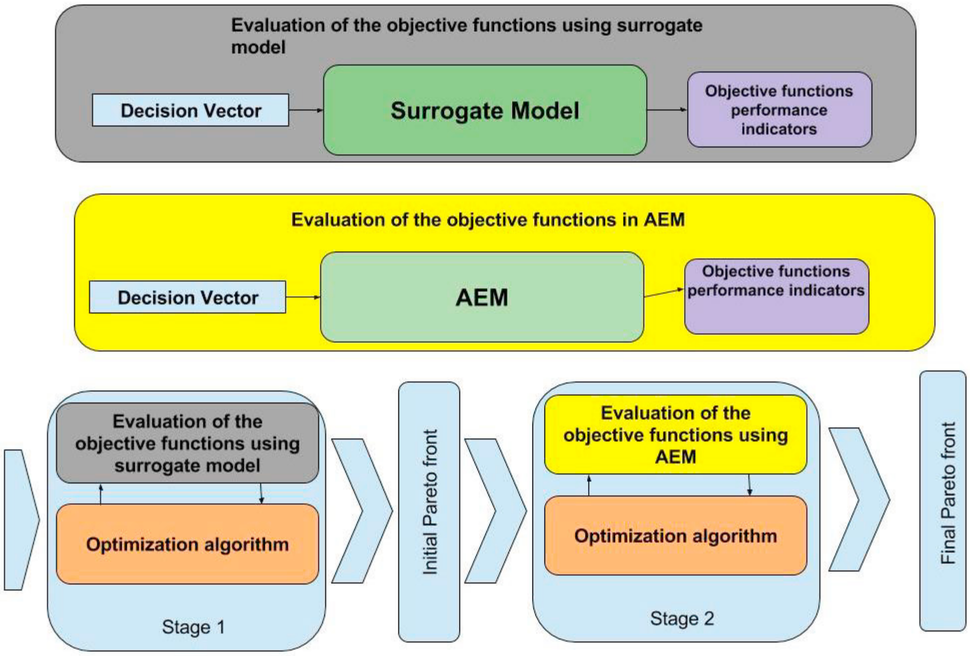

Fig.2: Overview of the SEM

4. Energy flow model and dispatch strategy

The energy flow model considers the hourly power generation using renewable energy technologies and ICG and the energy interactions with energy storage and grid. Hourly renewable energy potential, state of charge of the battery bank and price of grid electricity are used to compute the operating load factor of the ICG and interactions with the grid and battery bank. Hourly wind speed at the height of an anemometer is taken to compute the hourly wind speed at wind turbine hub level. Power law approximation is used to consider the atmospheric boundary layer when computing the wind speed at wind turbine hub level. Hourly wind speed at the wind turbine hub level is used to calculate hourly power generation from the wind turbines. Cubic spline interpolation functions [5] are used to map the power curve characteristics into the wind turbine model. Similarly, hourly horizontal solar irradiation data are taken for the location and converted into tilted global solar irradiation using an-isotropic model [6]. Hourly tilted solar irradiation is used to compute solar PV power generation using Durisch model [7]. The specialty of the

Durisch model is that it considers factors such as global solar irradiation on the PV panel, temperature of the solar cell, air mass and the type of solar panel when computing the efficiency of the solar panel. A detailed description about the energy flow model can be found in Ref. [8]–[12].

Power generation using ICG, interactions with the storage and the grid are obtained using the dispatch strategy. A bi-level dispatch strategy introduced by Perera et-al [1], [13], [14] is used in this study. Operating load factor of the ICG is determined in the first level of the dispatch strategy using fuzzy logic. Afterwards, the mismatch between demand and generation is computed. The interactions between grid and energy storage are determined subsequently considering the TOU price of electricity in the grid, grid curtailments and the state of charge of the battery bank using finite state machines. The Markov decision model is used to evaluate the performance of the system throughout the year on an hourly basis (8760 steps). Based on that, the life time of the battery bank and ICG and other operation costs were determined.

Initial capital investments for the system and the operation costs were considered in the cost model. Initial cost consists of acquisition cost of system components and installation costs. Operation consists of two parts i.e. fixed annual operational cost (FAO) and variable operating cost (VOC). FAO considers the maintenance cost for SPV panels and wind turbines, expenses for the fuel and operation of ICG, expenses for grid interactions etc. VOC consists of replacement cost for ICG and battery bank. Finally, the net present value of all the cash flows is taken and used to compute Levelized Energy Cost (LEC), which is taken as the objective function for the optimization. Similarly, hourly simulation of the energy system is used to compute the loss of load probability of the energy system (LOLP) and Levelized CO2 emissions (LCO2). LEC and LCO2 are taken as the objective functions for the Pareto optimization. LOLP is considered as a constraint in the optimization.

5. Surrogate model to present the energy system

The surrogate model has 21 input variables and 3 output variables. Three candidate methods, namely linear regression, regression support vector machine and artificial neural network were used to model the relationship between these input and output variables. The accuracy of each of the candidate methods was evaluated using the mean squared error (Eq. 1). In this equation y_i is the output from the AEM for the i^{th} test point and $\hat{y}_i$ is the output from the surrogate model. $k\ (\in \{1,2,3\})$ corresponds to the output variable being evaluated and N is the size of the test set.

$$error_{model}(k) = \frac{1}{N}\sum_{i^{th}\ test\ point}(y_i - \hat{y}_i)^2 \quad (1)$$

Out of the three candidate methods, the artificial neural network had the lowest mean squared error for all three output variables. Therefore, it was selected to be used as the surrogate model. The final neural network is a fully connected network that consists of two hidden layers, with each layer consisting of 50 neurons. The *Tansig* transfer function is used for the neurons in the hidden layer and for the output layer a linear transfer function is used. The model was trained on a dataset with 640’000 training samples and Levenberg-Marquardt backpropagation was used to train the network.

6. Optimization algorithm

Formulation of objective functions is not straight forward when using AEMs. Furthermore, mapping of decision space variables using surrogate models results in non-convex functions in most of the instances (especially when using artificial neural networks). Heuristic algorithms perform better when optimizing objective functions which are neither linear nor analytical nor convex. An evolutionary algorithm is used in this study to conduct Pareto multi objective optimization considering GHG emission and Levelized energy cost as objective functions. E steady ε-state evolutionary algorithm based on the hyper volume technique is used as the optimization algorithm [15]. Simulated Binary crossover and Polynomial mutation operators [16] are used as the operators for the optimization. Constraint tournament method is used to handle the constraint in the optimization. A detailed description of the optimization algorithm can be found in Ref. [10].

7. Results and Discussion

Initially, the surrogate model developed is used to predict the two objective functions and the constraint used in the optimization problem. Subsequently, the same neural network architecture is used and trained for eight different output variables. When analyzing the results it is clear that the surrogate model can be effectively used for most of the output variables. When considering the two objective functions and the constraint considered for the optimization output, variables one and three perform better than output variable 2.

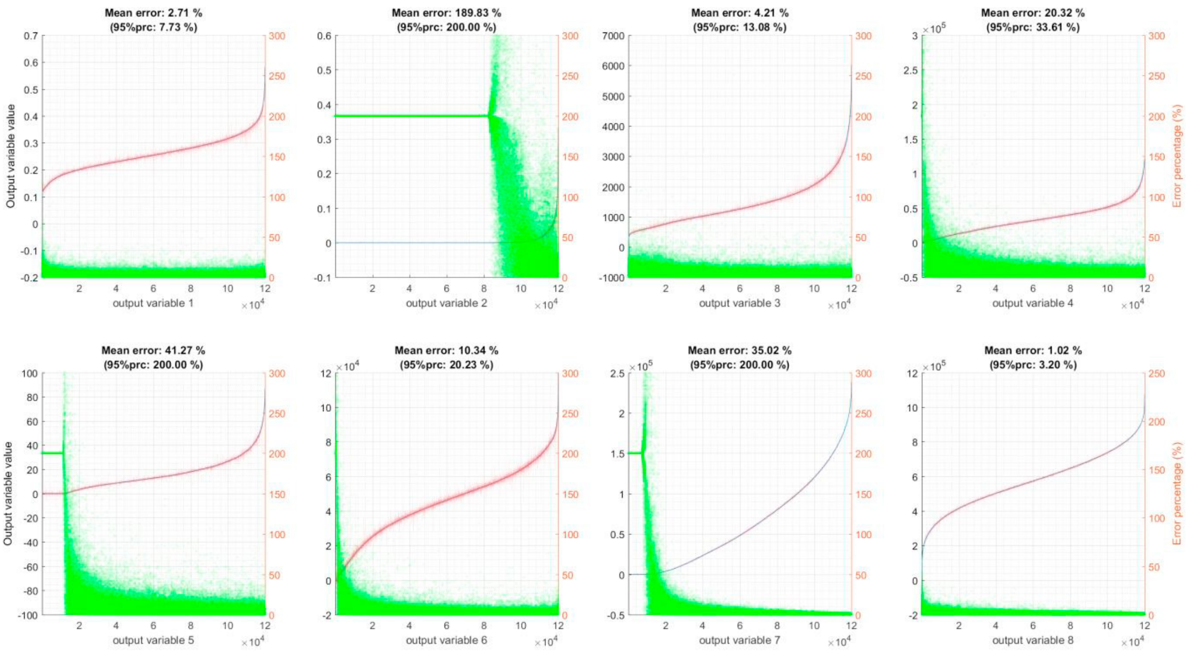

Fig.3 comparison of Surrogate model with AEM

Using the surrogate model developed, a Pareto optimization is conducted and a Pareto front is obtained considering LEC and LCO2. Four design solutions from the Pareto front are taken and presented in Table 1. As expected, LCO2 notably increases with the reduction of cost. When considering the design solutions, it is prudent that S2 and S4 are having the same system configuration. However, the LCO2 emissions show a significant difference in emissions. This is mainly due to the changes in operation strategy.

Table 1:Selected Design solutions from the Pareto front

Solution	Levelized Cost of Energy ($)	Levelized CO_2 Emissions (10^3 Kg)	Capacity of SPV panels (kW)	Capacity of wind turbines (kW)	Number of battery banks
S1	0.20	575	78	55	20
S2	0.24	536	113	80	18
S3	0.18	810	32	130	3
S4	0.30	474	113	80	18

8. Conclusion

This study presents a novel method to combine surrogate models with AEMs. An artificial neural network is used to develop the surrogate model in order to replace the actual engineering model. The surrogate model can help to map the decision space variables into the objective space with a substantial accuracy. Pareto optimization is conducted combining both a surrogate model and the actual engineering model. When considering the computational time, surrogate models can help to minimize the computational time notably.

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