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HYBRID ENERGY STORAGE SYSTEM DESIGN

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***Abstract*—*The necessity of hybrid energy storage system design is shown. It is considered the main components of hybrid energy storage systems and their features. It is shown that these systems are characterized by a beneficial coupling of two or more energy storage technologies with supplementary operating characteristics. The hybrid energy storage systems may include super capacitors, flywheels, superconducting magnetic energy storage, lithium-ion batteries, fuel cells. It is analyzed the use of every possible component as a part of the hybrid energy storage system in different operating conditions. It is considered a sizing methodology optimization for hybrid energy storage systems based on blast algorithm and hybrid neural networks.*

Index Terms—Hybrid energy storage system; super capacitors; flywheels; lithium-ion batteries; fuel cells; blast algorithm; hybrid neural networks.

I. INTRODUCTION

Global energy challenges and their impact on the environment have accelerated the adoption of renewable energy sources and development of smart and efficient micro-grid technologies. Low voltage micro-grid in particular has attracted increasing attentions from researchers. Micro-grid is a small-scaled autonomous power grid system that consists of multiple energy generations from renewable and non-renewables resources, energy storage systems (ESS) and power electronic converters [1].

Unlike the grid-connected micro-grids that have virtually unlimited support from the high inertia power generators, standalone micro-grids leverage heavily on its ESS to balance the mismatch between the power it generates and the power being consumed. The ESS acts as buffer to store surplus energy and supply it back to the system when needed. Energy storage systems in standalone micro-grid also play an important role in regulating instantaneous power variations and maintaining power quality.

In standalone micro-grid, the power flows in and out of the ESS elements varies widely depending on the instantaneous power generation and load condition. In general, the power exchanges in ESS can be categorised into high-frequency components such as sudden surge in power demand or intermittent solar power generation on a cloudy day, and the low-frequency components such as natural behaviour of renewable energy resources or daily average energy consumption pattern. High-frequency power exchanges generally require ESS elements with fast response time, while low-frequency power exchanges require high energy density ESS elements.

According to Bloomberg New Energy Finance estimates, the installed storage capacity in the world will grow to 1.095 GW in 2040. During this time, $ 662 billion will be invested in the industry. The International Energy Agency predicts that the capacity of industrial storage by 2040 will amount to 330–550 GW. At the same time, the cost of storage will decrease – the prices for lithium-ion batteries are expected to fall by half by 2030 compared to 2020. In the future, 10 years, the storage may become more cost-effective than gas turbine units, which are now used to balance power systems.

II. HYBRID ENERGY STORAGE SYSTEM

Based on the characteristics of the different ESS elements (Table I), none of them has the characteristics to respond optimally to both high and low frequency power exchanges [2]. One way to get around this limitation is by combining multiple types of energy. storage elements to form a hybrid energy storage systems (HESS) [1].

Hybrid energy storage systems are characterized by a beneficial coupling of two or more energy storage technologies with supplementary operating characteristics (such as energy and power density, self-discharge rate, efficiency, life-time, etc.) [3]. It's very often they are an effective way to improve the output stability for a large-scale photovoltaic (PV) power generation systems. It is connected with the

PV output fluctuations (high- and low frequency) that require an energy storage system with both high power density and high energy density for securing large-scale penetration, influenced by highly fluctuated load. The power management is designed to increase HESS efficiency by avoiding battery operating at low power levels. HESS includes high power storage (HPS) and high energy storage (HES). High power storage systems are suitable for smoothing out high frequency fluctuations but they are very expensive that restrict their large-scale application. High energy storage systems are cheaper than HPS systems and have large storage capacity and are suitable for smoothing out low frequency fluctuations. High power storage mainly includes supercapacitors (SC), flywheels, superconducting magnetic energy storage (SMES), etc.; while HES mainly includes pumped hydro, compressed air, vanadium redox flow batteries (VRB), sodium-sulfur cells, lead-acid cells (PbAc), the most modern lithium-ion batteries (Li-ion, fuel cells (FC) (FC is electrochemical device that is able to convert the chemical potential into an equivalent electrical potential), etc.

TABLE I. CHARACTERISTICS OF DIFFERENT ESS ELEMENTS [8]

Energy storage system	**Energy density**	**Power density**	**Cycle life**	**Response time**	**Cost**
chemical battery	high	low	short	medium	low
sodium-sulphur (NaS) battery	medium	low	short	slow	medium
flywheel	low	high	long	fast	high
supercapacitor	low	high	long	fast	medium
superconducting magnetic energy storage	medium	high	long	fast	high

There are some important problems, connected with HESS, especially design (multi-objective sizing methodology for hybrid energy storage systems, selection of energy storage systems by comparing multiple energy storage combinations, optimal life cycle solutions considering the effects of multiple weather conditions,) and control (coordinated control to eliminate the different term fluctuations by using capacitor and battery).

III. HYBRID ENERGY STORAGE SYSTEM COMPONENTS FEATURES

The most promising type of battery is lithium-ion batteries (Li-ion). Compared to other types of electrochemical storage batteries, Li-ion has the highest specific energy capacity (120–200) W·h/kg. In addition, they have good load characteristics and undemanding to service. They do not have a “memory effect”, they do not require control and training cycles. In the production of powerful batteries consisting of several cells, a very low internal resistance of the cells gives a great advantage.

Supercapacitors are advanced capacitors, working at constant voltage, and able to store hundreds of times more energy, giving it at the right time in the form of large currents [5] their specific energy consumption is 10–50 times lower than that of Li-ion batteries. The energy storage process in the SC is carried out by charge separation on two electrodes with a sufficiently large potential difference between them. Since chemical transformations of substances do not occur during SC operation (if charging voltages are not exceeded), the system resource can exceed 100,000 discharge charge cycles. Supercapacitors belong to the category of short-time storage devices and compete with flywheels and SMES, however, they are more compact and simple [5].

As you know, SMES can solve the following multifunctional tasks: increase limits of the transmitted power of the line according to the conditions of dynamic and static stability, damping of electromechanical processes in the power system in after emergency conditions, smoothing irregular power fluctuations along the lines, connecting power systems, reactive power consumption management, etc.

Flywheels on an industrial scale are used to stabilize power surges. A preliminary assessment of the parameters of developed and promising flywheel drives allows us to consider them as a means of increasing the dynamic stability of the generator.

A fuel cell is an electrochemical cell that converts the chemical energy of a fuel (often hydrogen) and an oxidizing agent (often oxygen) into electricity through a pair of redox reactions. Fuel cells are different from most batteries in requiring a continuous source of fuel and oxygen (usually from air) to sustain the chemical reaction, whereas in a battery the chemical energy usually comes from metals and their ions or oxides that are commonly already present in the battery, except in flow batteries. Fuel cells can produce electricity continuously for as long as fuel and oxygen are supplied [4].

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It is considered an optimization sizing methodology for hybrid energy storage systems.

IV. Blast Algorithm for Hybrid Energy Storage System Optimization

The main difficulty in solving engineering optimization problems with a large number of local optima is the preliminary convergence of the algorithms. It consists in the fact that for a multimodal function, the solution may be a local optimum, which delivers a nonoptimal value. At the level of the genetic algorithm, the convergence problem is partially solved by using various options for parameters and their modifications.

The general trend in the study of these algorithms is increasingly the use of combined parameter methods. In this case, it is important to combine a preliminary knowledge of the tasks to be solved and preliminary results, as with the reverse descent algorithm.

The main advantage of genetic algorithms lies precisely in the fact that they can significantly overcome these difficulties.

Population-based multi-agent algorithms work with a set of potential solutions. Each decision is gradually improved and evaluated, thus, each potential decision influences how other solutions will be improved. Most population methods borrowed this concept from biology: the process of finding the best solution "copies" a certain natural process or the behavior of certain animal species, and their species characteristics are taken into account.

The class of complex systems, referred to as flock type algorithms, is also often used the term "bionic algorithms", a rich source of non-standard numerical methods with which you can solve complex problems when there is not enough information about the optimized function.

It should also be noted that most flock type algorithms originally designed to solve unconditional optimization problems with real variables, and they all have some parameters that it is necessary to select when solving a particular problem (the most significant “parameter” in this sense is the size of the population of potential solutions). However, studies have shown that it is impossible to determine in advance which it is from these algorithms that should be applied to solve one or another optimization task, in addition, as already mentioned, for each the algorithm you need to choose in advance the size of the population of potential solutions, which in turn is also a challenge.

An optimization problem can be studied in two states, i.e., having continuous and discrete variables, while mixed problems can also be found in the literature. In continuous problems, each decision variable can vary continuously within upper and lower bounds, while in the case of discrete problems, the design variables are chosen from a specific set.

The proposed method is called mine blast algorithm (MBA), and is based on mine bomb explosions in real life situations [6], [7].

Here it is considered structural optimization with discrete variables, which can be presented as follow.

$$\underset{x_1, x_2, \dots, x_n}{\text{extr}} f\left(x_1, x_2, \dots, x_n\right),$$

with restrictions $g_j\left(x_1, x_2, \dots, x_n\right) \le 0,\ j = \overline{1, m},$ where battery parameters: battery technology used, discharge power, nominal battery capacity; super capacitor: energy storage, time of charging, cycle life, warranty; fuel cells: type, power banks.

The idea of this algorithm is based on observation of a mine bomb explosion, in which the thrown pieces of shrapnel collide with other mine bombs near the explosion area resulting in their explosion. To understand this situation, consider a mine field where the aim is to clear the mines. Hence, the goal is to find the mines, while the most important is to find the one with the most explosive effect located at optimal point X^* which can cause the most casualties (min or max $f(x)$ per X^*). The mine bombs of different sizes and explosive powers are planted under the ground. When a mine bomb is exploded, it spreads many pieces of shrapnel and the casualties ($f(x)$) caused by each piece of shrapnel are calculated. A high value for casualties per piece of shrapnel in an area may indicate the existence of other mines which may or may not have higher explosive power [6].

Each shrapnel piece has definite directions and distances to collide with other mine bombs which may lead to the explosion of other mines due to collision. The collision of shrapnel pieces with other mines may lead us to discover the most explosive mine. The casualties caused by the explosion of a mine bomb are considered as the fitness of the objective function at the mine bomb's location. The domain (mine field) solution may be divided into infinite grid where there is one mine bomb in each portion of the grid.

The given algorithm starts with an initial point(*s*) called first shot point(*s*). The first shot point is represented by X_0^f. The superscript f refers to the number of first shot point(*s*) ($f = 1, 2, 3,...$), where f is user defined parameter. This algorithm requires an initial population of individuals as is the case with some metaheuristic methods. This population is generated by a first shot explosion producing a number of individuals (shrapnel pieces). In this paper, one first shot point was used (as an initial point).

Increasing the number of first shot points increases the initial population and results in an increase in the number of function evaluations (and computational time). In addition, the increase in first shot points did not offer significant improvement in the optimization process for the problems examined in this paper.

The choice of first shot point(*s*) may lead the algorithm to search the solution space for different locations. In addition, it may be no need for entering the first shot point(*s*). The proposed algorithm can also randomly choose the location(*s*) of the first shot point(*s*), without being specified by the user. If the first shot point(*s*) is in infeasible region, the algorithm uses the lower bound value given by a problem and modifies the first shot point value by a small randomly generated value to perform a new first shot. The full version of MBA is represented in papers [7], [8].

This task also can be considered as classification problem when we analyze the different variants of HESS. Then we can use artificial neuron networks, especially hybrid neuron networks.

V. Structural-Parametric Synthesis of an Ensemble of Neural Networks

An ensemble of neural networks is a group of topologies united in a single structure, which may differ in architecture, learning algorithm, learning criteria and types of forming neurons [9] – [12]. In another variant, the term is understood as an ensemble "combined model", the output of which is a functional combination of outputs of individual models [13].

Input data can be divided into specific groups for processing by different ANN or fed to all networks at the same time.

Forming ensembles of ANN, it is necessary to optimize two criteria – quality training of separate ANN and their optimum association.

Known algorithms are usually divided into two classes [11]: algorithms that for new classifiers change the distribution of training examples, based on the accuracy of previous NNs (busting), and those in which new members of the ensemble learn independently of others (beging).

The main difficulty of networking in an ensemble is learning all the components to solve a problem. In order to increase the effectiveness of training, NNs are trained separately (if possible) and then combined into a single structure. However, if the tuning algorithms of the selected topologies belong to different classes of training, synchronous training of all the NNs belonging to the ensemble is required, and therefore it is necessary to develop a single algorithm of tuning of all the NNs of the ensemble.

We use a parallel ensemble structure with a layer of integration.

In the our case, an ensemble topology based on individual neural networks is used, in particular: Perceptron, Radial-basis function network (RBFN), counter propagation network (CPN), probability neural network (PNN), NefclassM, NaïveBayes.

The number of samples in the set is 178. Each object has 13 features, represented by real numbers greater than zero, and one class label. The number of classes is 3. For the test sample, 20% of the data set was selected, respectively, 80% for training.

The Results are presented in Table II.

TABLE II. Learning Results of Individual Networks

Base NN	***Train***	***Test***
Perceptron	27.46%	38.89%
RBFN	38%	38.89%
CPN	40.14%	38.88%
PNN	91.54%	86.11%
NEFClassM	80.28%	80.55%
Naïve Bayes	93.66%	94.44%

IV. Conclusions

It is considered the hybrid energy storage system design. Different composition of HESS analized. It is shown that the basic components of HESS are super capacitors, flywheels, superconducting magnetic energy storage, lithium-ion batteries, fuel cells. Two approaches are proposed for optimization problem solution of HESS design task: blast algorithm and ensemble of neural networks. The ensemble of neural networks is used as a mean of classification task solution.

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В. М. Синєглазов, І. О. Юденко. Проектування гібридної системи зберігання енергії
Показано необхідність створення гібридної системи накопичення енергії. Розглянуто основні компоненти гібридних систем накопичення енергії та їх особливості. Показано, що ці системи характеризуються вигідним поєднанням двох або більше технологій накопичення енергії з додатковими експлуатаційними характеристиками. Гібридні системи накопичення енергії можуть включати у себе суперконденсатори, маховики, надпровідні накопичувачі магнітної енергії, літій-іонні акумулятори, паливні елементи. Проаналізовано використання кожного можливого компонента в складі гібридної системи накопичення енергії в різних умовах експлуатації. Розглянуто оптимізацію методології визначення розмірів для гібридних систем накопичення енергії на основі алгоритму вибуху і гібридних нейронних мереж.

Ключові слова: гібридна система зберігання енергії; суперконденсатори; маховики; літій-іонні акумулятори; паливні елементи; алгоритм вибуху; гібридні нейронні мережі.

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В. М. Синеглазов, И. А. Юденко. Проектирование гибридной системы хранения энергии

Показана необходимость создания гибридной системы накопления энергии. Рассмотрены основные компоненты гибридных систем накопления энергии и их особенности. Показано, что эти системы характеризуются выгодным сочетанием двух или более технологий накопления энергии с дополнительными эксплуатационными характеристиками. Гибридные системы накопления энергии могут включать в себя суперконденсаторы, маховики, сверхпроводящие накопители магнитной энергии, литий-ионные аккумуляторы, топливные элементы. Проанализировано использование каждого возможного компонента в составе гибридной системы накопления энергии в различных условиях эксплуатации. Рассмотрена оптимизация методологии определения размеров для гибридных систем накопления энергии на основе алгоритма взрыва и гибридных нейронных сетей.

Ключевые слова: гибридная система хранения энергии; суперконденсаторы; маховики; литий-ионные аккумуляторы; топливные элементы; алгоритм взрыва; гибридные нейронные сети.

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