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Degree of Optimality as a Measure of Distance of Power System Operation from Optimal Operation

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Abstract *- This paper presents an algorithm based on inter-solutions of having scheduled electricity generation resources and the fuzzy logic as a sublimation tool of outcomes obtained from the schedule inter-solutions. The goal of the algorithm is to bridge the conflicts between minimal cost and other aspects of generation. In the past, the optimal scheduling of electricity generation resources has been based on the optimal activation levels of power plants over time to meet demand for the lowest cost over several time periods. At the same time, the result of that type of optimization is single-dimensional and constrained by numerous limitations. To avoid an apparently optimal solution, a new concept of optimality is presented in this paper. This concept and the associated algorithm enable one to calculate the measure of a system's state with respect to its optimal state. The optimal system state here means that the fuzzy membership functions of the considered attributes (the characteristics of the system) have the value of one. That particular measure is called the "degree of optimality" (DO^{system}). The DO^{system} can be based on any of the system's attributes (economy, security, environment, etc.) that take into consideration the current and/or future state of the system. The calculation platform for the chosen electric power test system is based on one of the unit commitment solvers (in this paper, it is the genetic algorithm) and fuzzy logic as a cohesion tool of the outcomes obtained by means of the unit commitment solver. The DO-based algorithm offers the best solutions in which the attributes should not to distort each other, as is the case in a strictly deterministic nature of the Pareto optimal solution.*

Keywords: Optimality, Fuzzy logic, Genetic algorithm, Unit commitment.

NOMENCLATURE

DO	Degree of optimality
ED	Economic dispatch
FL	Fuzzy logic
GCR	Generation capacity reserve
GA	Genetic algorithm
LIM	Lambda iteration method
MILP	Mixed-integer linear programming
PF	Profit
RV	Revenue
TC	Total cost
UCP	Unit commitment problem

1. INTRODUCTION

1.1. The term optimal - general

The term "optimal" signifies being in the best shape, position, or state in the present circumstances. Optimality arises from the interaction of conflicting constraints. The overall philosophy of a multi-objective optimization is based on the Italian economist Pareto's concept used in his studies of economic efficiency and income distribution. That concept takes into account the fact that a system's state cannot be improved if the increase of at least one of the objective functions f_i, with i=1,2,...,n, endangers the other objective functions. In other words, no characteristic should be improved if it endangers the other characteristics.

There are numerous approaches and algorithms that attempt to solve the multi-objective problems. Some of these approaches translate the multi-objective problem into one single-objective scalar function, such as the scalarization technique [1] or the ε-constraints method [2]. However, in the first technique, there is a problem with determining the weight parameter as well as a significant computation time. The second technique is not efficient if the number of objective functions is greater than two. Other optimization techniques are meant to solve multi-objective problems either through goal programming and multi-level programming or through an artificial intelligence and simulated nature

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processes such as those of bee [3] and ant [4] colonies, which are especially effective for the non-continuous multi-objective problems. In these cases, some other techniques should be applied, such as integer programming including different combinatorial optimization techniques [5].

1.2. The optimality of power system operation

Optimization of power and energy systems may suffer from problems which arise from the fact that power systems contain a huge number of variables leading to non-continual multi-objective problems. In [6], the applications of the optimization of electric power systems are presented. They include a UCP, ED, optimal maintenance, and optimal power flow. The optimization methods are based on linear, non-linear, integer, dynamic, and separable programming. Some of the mentioned methods will satisfy the planning and operational demands of power system operatives. Special problems arise when it is necessary to find an optimal solution for a system under the circumstances of a significant number of constraints and several goals.

The problem of optimality and optimal operation of a power system can be solved in the framework of a parallel-interactive calculation based on the methods of a single/multiple goal(s) and a constraint optimization. A single objective cannot satisfy the needs of planners and other decision-makers. At the same time, the multi-objective optimization must take into account the conflicts of the goals. Neither of the optimization approaches can afford a solution without complicated mathematical procedures that frequently have problems with convergence and can give ambiguous results. The constraints, which narrow the range of values of an objective function in a multi-objective optimization, are integrated as a penalty costs into the objective (fitness) function. In these cases, there is a problem with the appropriate values associated with the penalties. In [7], the UCP is based on an objective function which includes, in addition to the minimal generation and start-up costs, the variability of wind energy availability, costs due to emission, and costs incurred due to penalties for not meeting a load demand or reserve targets. This approach does not provide the possibility of finding the component which affects the objective function. The approach in [8] also deals with the uncertainties in the UCP but suffers the same problems that appear in [7].

In the field of power system operation optimization there are numerous published works. Some of them include FACTS devices allocation or combined economic dispatch and reliability in power system using an improved particle swarm optimization for optimal operation of power systems [9]-[10]. Another one work uses Monte Carlo simulation in probabilistic multi-objective optimal reactive power dispatch considering load uncertainties [11]. All these works are based on one of the power system operation aspects and not treat the power system as one unique space.

However, the proposed DO-based algorithm enables one to incorporate a view into the inter-medium solutions. In such a way, the sub-optimal solutions can sometimes be chosen. The advantage of the DO-based algorithm with respect to the MILP is the possibility to take into account a significant number of different constraints (linear, non-linear, and binary). The MILP may be difficult to utilize due to the cost of identifying a huge number of constraints and the impossibility of having them built into the model.

The GA and LIM have been used in the DO-based algorithm as the solvers for UCP and for ED, respectively, but other UCP solvers can also be applied, such as other iterative optimization methods, including the descent methods and Newton's method. Then, the approaches of optimization such as MILP [12] or mixed-integer quadratically constrained program [13] can be used. It is important that the UCP solvers introduced in the DO-based algorithm have iterative character where for each of iterations the other aspects of power system operation can be calculated. In this way, the UCP and ED inside of the power systems with numerous generating units and their constraints can be solved with respect to all the considered system attributes (technical, economy, and environmental attributes in the short-term analysis, and for long term studies, the portfolio development attributes).

1.3. The aim and contribution of the proposed approach

The optimization algorithms that are primarily used in the industry include MILP, based on the branch-and-bound solver as shown in Fig. 1 and is encompassed by LINGO [14]. The MILP is a good tool for optimizations, however it is unable to handle with unsecure, unreliable and hard-tuned variables.

The DO-based algorithm is a one-way algorithm as shown in Fig. 2 and based on the variables represented through the fuzzy functions, which allow a greater degree of freedom of understanding their nature and acceptability of solutions.The DO-based algorithm is a parallel-interactive procedure which scales the conflicts of the decision-makers’ goals by offering the intermediate and acceptable solutions. The presented algorithm offers a way of measuring a system’s state with respect to its optimal state. An optimal system state here means that the fuzzy membership functions of the considered components have the value of one. Such a measure is called the "degree of optimality" (DO^{system}). The DO^{system} can be based on any of the system's attributes (economy, security, environment, etc.) which take into consideration the current and/or future state of the system. The calculation platform is based on one of the UCP-solvers (herein, the genetic algorithm) and fuzzy logic is conducted through several iterations searching for the best solution with respect to the state of the entire system.

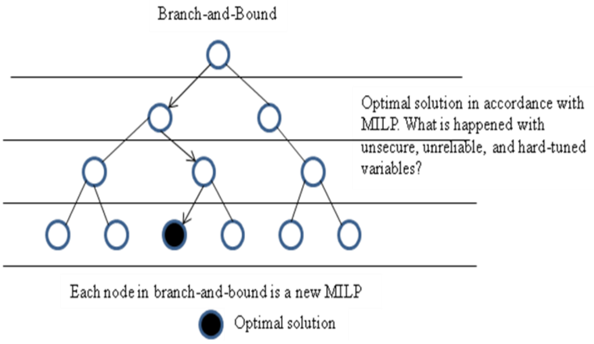

Fig. 1. The MILP-based algorithm.

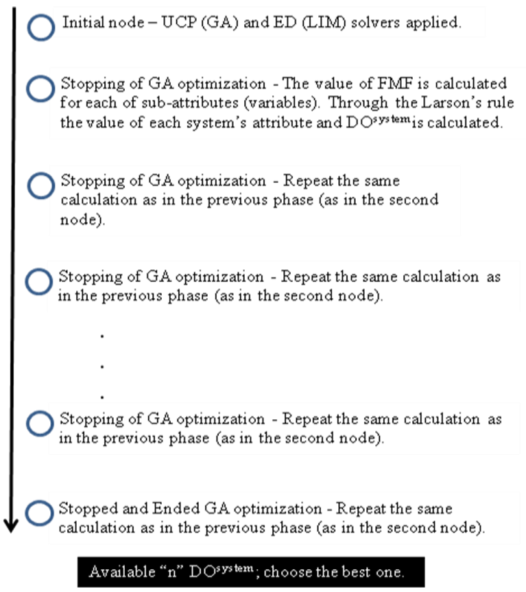

Fig. 2. The DO-based algorithm.

The DO encompasses the variables that are of crucial importance for the system state operation. Many of these variables can be calculated or measured. It is of interest to find out how far the system is from optimality with respect to the disposable variables that describe one system in a power system, such as electric power generation cost, transmission line power flows, CO_2 emission, generator load angle positions, profits, etc. The DO-based algorithm can be viewed as a multi-level optimization problem, similar to the bi-level-based optimization [15]. Bi-level problems have been widely studied in the field of classical and evolutionary optimization [16]. These studies show computational inefficiency and a need for theoretical and methodological improvements to efficiently handle the problems associated with bi-level optimization [17].

Similar to the bi-level-based optimization, the DO-based algorithm includes two stages of optimization (upper and lower level problems, or inner and outer problems). The first stage uses the UCP solver to minimize the generation cost, i.e., it only considers a purely economic aspect of a generator dispatch. The second stage uses the results of the first stage and calculates the generation capacity reserve, CO_2 emission, profit from the generators, and other sub-attributes of the economy, technical, environment, and security attributes that can be of interest to the system planners and operators. These sub-attributes are presented through a fuzzy membership function (FMF) taking into account their optimal states defined by the planner and operator themselves or through a sub-attribute-based single-objective optimization.

The optimization problem can be formulated as follows:

$$\min_{x_{a1},x_{a2},\ldots,x_{an}}\left[-DO\left(x_{a1},x_{a2},\ldots,x_{an}\right)\right] \qquad (1)$$

so that

$$x_{DO}\in \operatorname{argmin}_{X_{DO}}\left\{\begin{array}{c} f\left(\begin{array}{c} x_{sa1}^{1},\ldots,x_{san}^{1},x_{sa1}^{2}, \\ \ldots,x_{san}^{2},x_{sa1}^{n},\ldots,x_{san}^{n}\end{array}\right): \\ X_A^L \le X_A \le A_A^U \\ \\ X_A = f\left(x_{sa1},x_{sa2},\ldots,x_{sai},\ldots x_{san}\right)\end{array}\right\}$$

$$x_a \in X_A; x_{sa}\in X_{SA}$$

Where X_A^L and X_A^U represent the lower and upper inequality constraints of the attribute X_A, respectively, x_{sai}^{i} the i^{th} sub-attribute in a fuzzy i^{th} attribute set, and X_A and X_{SA} are the fuzzy sets of the attributes and sub-attributes, respectively. The equality constraints are not shown in the formulation here because they are a part of the UCP solution. Used as an aggregate measure, the DO^{system} describes the outcomes of a particular system's region or of an entire system. The concept of the DO^{system} is based on comparing the current operational system state with an optimal one. The DO^{system} is an accurate reflection of a) whether the states changed in particular circumstances, b) contingency interventions, and c) the planned activities, all with reference to the optimal state.

To compare the proposed algorithm with a well-known MILP, we shall first present here a form of the problem subjected to the MILP procedure:

Objective: minimize $c^T X$
Constraints: $A X = b$ (linear constraints) (2)
$l \leq X \leq u$ (bound constraints)
some or all X_j must take integer values (integrality constraints)

and, afterwards, a form subjected to the DO-based procedure

Objective: minimize $c^T X_A$ via GA and LIM per one of the system's attribute
1. Stop the GA and LIM after *n* iterations
2. Calculate the Fuzzy Membership Function (FMF) for the chosen attribute
3. Calculate the FMFs for additional system's attributes (X_B, X_C,…,X_N):
(There are no constraints on set of system's attributes and these attributes may take any type of values (integer, non-integer, binary, etc.) (3)
4. Continue the GA and LIM
5. Repeat steps 1 to 3
6. If (GA and LIM reached the goal per X_A) then Repeat steps 2 to 3; end
elseif (GA and LIM not reached the goal per X_A);go to 4
end

As seen, the objective function in the MILP procedure takes into account the variables presented in the constraints. The DO-based procedure takes one variable (one X_A, for example, economy, and one sub-attribute inside of X_A, for example, profit), but extends the calculation after each branching (or accepted number of iterations if the GA is used as a UCP solver) by additional calculations that take into consideration the fuzzy nature of the other attributes. In that way, the long-term calculation or infeasibility in obtaining a solution (which may be the case with MILP) is avoided by the DO-based approach. The rest of this paper is organized as follows. In Section 2, the algorithm on DO-based concept is developed. Formulation of the fuzzy model of profit, generation capacity reserve, and CO_2 emission as the represents of system's attributes of economical, security, and ecological nature is presented in Section 3. Numerical simulation and results are presented in Section 4. Finaly, in Section 5 the conclusions are presented.

2. ON THE DEGREE OF OPTIMALITY ALGORITHM

The DO-based algorithm produces the degree of optimality of each of the considered power system attributes that in fact together form the multi-objective problem, Fig. 3. The power system attributes can be divided into technical, economy, and environmental attributes in the short-term analysis, and in long term studies, the portfolio development attributes can be added. The technical attribute encompasses the sub-attributes such as load angles, power losses, voltage profiles, and generation capacity reserve. The economy attribute encompasses the sub-attributes such as power generation costs and profits from generating units. The environmental attribute encompasses the sub-attributes such as CO_2 emission and SO_x emission. The portfolio development attributes evolve the sub-attributes such as the participation of renewable energy sources in the energy system, inclusion of a demand response program and energy storage capacities. The mentioned attributes and sub-attributes are not isolated, but have an interaction between them.

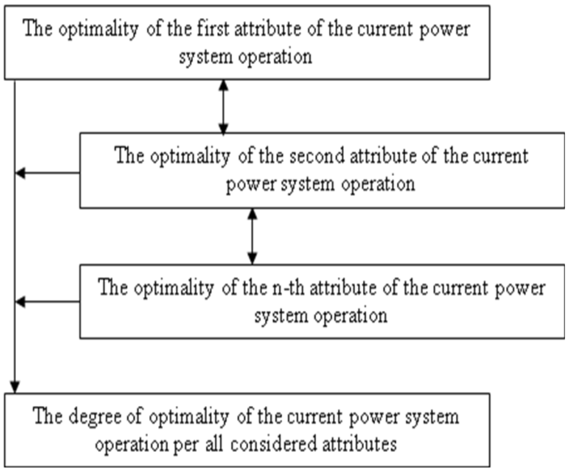

Fig. 3. The structure of DO for a current power system operation.

The DO-based algorithm presented here uses the GA and the LIM as tools for solving the UCP [18] and ED, respectively. The GA is used as a heuristic method for general mixed-integer problems. Other methods such as simulated annealing could also be used. The objective of the UCP and ED is to minimize the total generation cost including the fuel, start-up, and shut-down costs. The algorithm used for the UCP and ED solutions goes to the end of the calculation, but stops whenever the difference between total costs of the ultimate and penultimate iterations is within a prescribed limit from zero, i.e.:

$$(COST_{ultimate\,iteration} - COST_{penultimate\,iteration}) < 10^{-6} \quad (4)$$

In our approach, we stop the optimization in each of the iterations, for which the values of various sub-attributes of the system attributes are calculated, such as the profits from the generators, generation capacity reserve, CO_2 emission, and load of the transmission lines. The results of these calculations are translated into the field of fuzzy logic, i.e., into the appropriate fuzzy membership functions of their fuzzy sets. The fuzzy values of the calculated sub-attributes for each of the system attributes individually are reduced through the Larson rule [19], giving the $DO^{attribute}$ for each of the system attributes: technical, economical, and environmental. The three DOs (reduced through the Larson rule as well) give the system's DO_1^{system}. Then, further iterations of the genetic algorithm are conducted. Afterwards, on the basis of the determined economical engagements of the generators, the various sub-attributes of the system attributes are again calculated, and, based on those results, the $DOs^{attribute}$ of the system attributes are calculated. Finally, through the fuzzy aggregation of all the given $DOs^{attribute}$, the system's DO_2^{system} is obtained. The algorithm is conducted until a desired number of iterations is reached or as long as Eq. 4 is satisfied. In both cases, the procedure is finished at DO_N^{system}, where N is the number of iterations. The maximum value of the DO_i^{system} (i=1,…, N) is selected and, on the basis of that solution, the fuzzy value of all the system attributes are identified, as shown in Fig. 4. Eventually, the maximum value of the DO_i^{system} makes it possible to know the following system sub-attributes: profit, generation capacity reserve, CO_2 emission, etc.

The optimal state of a system is characterized with the DO^{system} equal to one. This value implies that each of the fuzzy membership functions in the fuzzy set of the relevant attributes are one. Unity is the most desirable value of the measured and calculated sub-attributes and it is the most desirable system state.

The main advantage of the algorithm is the possibility of finding the DO^{system} for each of the pre-determined number of iterations of the GA (or any other UCP-solver which only aims at one goal), as well as for the attributes and sub-attributes. As the chosen fuzzy membership functions have constant values for a broader range of the sub-attributes' values, the $DO^{sub\text{-}attribute}$ can be updated without endangering either the DO of the other sub-attributes and attributes, or the DO^{system} in its entirety.

3. ON THE FUZZY MODEL OF PROFIT, GENERATION CAPACITY RESERVE, AND CO_2 EMISSION

To find the corner points of the fuzzy membership functions of the relevant sub-attributes, the UCP is considered as a single-objective optimization problem. In this case, the objective functions representing the relevant sub-attributes particularly refer to the profit from thermal generating units, generation capacity reserve (spinning reserve), and CO_2 emissions.

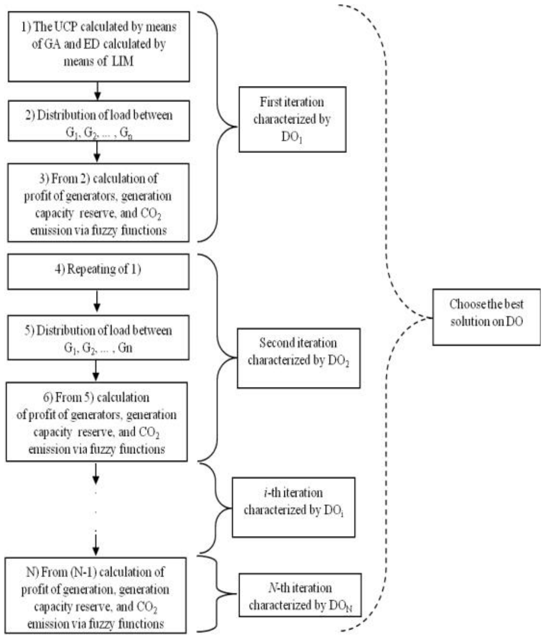

Fig. 4. The degree-of-optimality based algorithm (the algorithm designed to find the largest DO^{system}).

The genetic algorithm applied in the UCP procedure has been modified in accordance with the needs of the problem and in the context of the possible states of the thermal power plant (the required minimum and maximum time of their engagement). To create the feasible solutions in the initial population, the chromosomes are generated on the basis of the replicable variations. At the same time, to create new solutions and to maintain the already current feasible solutions, the crossing operators per blocks of T-hours and intelligent forward/back mutations are introduced [20].

3.1. The fuzzy model of profit from electric power generation

The fuzzy model of profit from electric power generation is based on the one-sided trapezoidal fuzzy set of profits characterized by its fuzzy membership function μ_{PF}, as illustrated in Fig. 5 and (5).

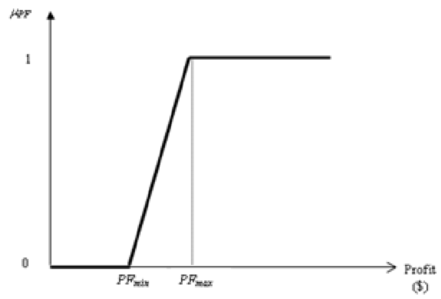

Fig. 5. The fuzzy set of profit.

$$\mu_{PF} = \begin{cases} 1 & PF \geq PF_{max} \\ \dfrac{PF - PF_{min}}{PF_{max} - PF_{min}} & PF_{min} < PF < PF_{max} \\ 0 & PF \leq PF_{min} \end{cases} \quad (5)$$

Profit (*PF*) = *RV*-*TC* ($),

RV – revenue, here taken as the product of the produced MWh and the price ($) of a MWh obtained as a result of the optimization directed only towards the maximal profit,

TC – total cost, here equal to the variable (fuel) cost (the constant cost such as labor cost, taxes, and the debt rate, can also be taken into consideration).

PF_{min} – minimal profit, determined from the UCP, taken as a goal of the optimization. The PF_{min} can also be determined in accordance with the criterion of covering the variable cost.

PF_{max} – maximal profit, determined from the UCP, taken as a goal of the optimization. The PF_{max} can also be determined in accordance with the criterion of an infra-marginal rent covering constant and variable costs.

3.2. The fuzzy model of generation capacity reserve

The fuzzy generation capacity reserve model is presented through the fuzzy set presented in Fig. 6 and Eq. (6).

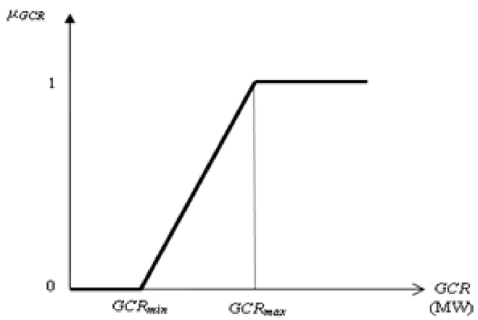

Fig. 6. The fuzzy set of the generation capacity reserve.

$$\mu_{GCR} = \begin{cases} 1 & GCR \geq GCR_{max} \\ \dfrac{GCR - GCR_{min}}{GCR_{max} - GCR_{min}} & GCR_{min} < GCR < GCR_{max} \\ 0 & GCR \leq GCR_{min} \end{cases} \quad (6)$$

GCR – current generation capacity reserve (difference between the nominal and the engaged electric power of generators) (MW).

GCR_{min} – minimal generation capacity reserve (spinning reserve) (MW), and

GCR_{max} – maximal generation capacity reserve (spinning reserve) (MW).

The algorithm to calculate the minimal and maximal generation capacity reserves is given in [21]. In the current study, the maximal and minimal values of the spinning reserve are to be 455 MW and 55 MW, respectively.

3.3. The fuzzy model of CO_2 emission

The fuzzy model of CO_2 emission is based on the form of the fuzzy set, as presented in Fig. 7 and Eq. (7). The CO_{2min} and CO_{2max} can be calculated through the optimization of the single-objective function where the objective functions are CO_{2min} and CO_{2max}.

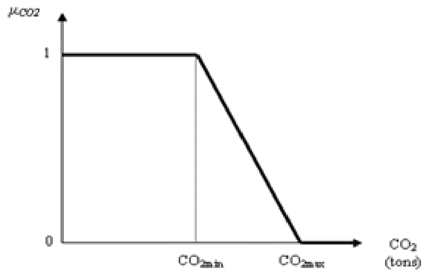

Fig. 7. The fuzzy set of CO_2 emission.

$$\mu_{CO_2} = \begin{cases} 1 & CO_2 \leq CO_{2min} \\ \dfrac{CO_{2max} - CO_2}{CO_{2max} - CO_{2min}} & CO_{2min} < CO_2 < CO_{2max} \\ 0 & CO_2 \geq CO_{2max} \end{cases} \quad (7)$$

CO_2 - current accumulated emissions of CO_2 (tons);

CO_{2min} - accumulated quantity of CO_2 emissions, which suggests a need of buying allowances for a future emission of CO_2;

CO_{2max} – accumulated quantity of CO_2 emission, which suggests that the future generation of electric power will not be profitable due to CO_2 penalties.

3.4. The fuzzy degree of optimality

The fuzzy degree of optimality is calculated using the Larson rule by multiplying the fuzzy membership functions of the sub-attributes together (profit, generation capacity reserve, and CO_2 emission), which belong to the system's attributes of economy, security, and environment, respectively as shown in Eq. (8):

$$DO^{system} = \prod_{i=\text{number of attributes}} \mu_i = \mu_{PF} \cdot \mu_{GCR} \cdot \mu_{CO_2} \quad (8)$$

The system's economy attribute is calculated on the basis of profits from all *n*-generators (or power plants) that are within the UCP solution.

$$\mu_{PF}^{attribute} = \prod_{g_i=\text{number of generators}} (\mu_{PF})_{gi} = (\mu_{PF})_1 \cdot (\mu_{PF})_2 \cdots (\mu_{PF})_n \quad (9)$$

Based on the UCP and economic dispatching results, the generation capacity reserve sub-attribute representing the security as the system's second attribute can be calculated as a sum of the spinning reserve of each of the generators scheduled to cover the current demand. The μ_{GCR} can be calculated in accordance with Eq. (6).

The system's environmental attribute of the power system operation is determined in accordance with CO_2 emissions of each of the engaged generators (power plants).

$$\mu_{CO_2}^{attribute} = \prod_{g_i = \text{number of generators}} (\mu_{CO_2})_{g_i} = (\mu_{CO_2})_1 \cdot (\mu_{CO_2})_2 \cdots (\mu_{CO_2})_n \quad (10)$$

4. CASE STUDY

The case study is conducted on the test system presented in [22] for a 24-hour time period, and the test system consists of ten generators. Table 1 presents the types of generators used, the maximal and minimal power outputs, and the cost coefficients of their cost functions. The data on the generators, given in Table 2, include CO_2 emissions (a_i, b_i, and c_i coefficients), minimal uptime/downtime of the generators (T_i^{up} and T_i^{down}), the costs of start-up from the hot and the cold state (hc_i and cc_i), the required number of hours during which the generator must be shut-down (cs_i), and identified number of hours in the on/off working regime ("+" for the on-state and "–" for the off-state). The shut-down costs of the generators are neglected in this analysis.

The forecasted hourly system load and the MWh-prices as a result of the optimization directed only at the maximal profit are presented in Table 3.

The objective is to find the system's the largest DO^{system} along the planning horizon as presented in Fig. 2. The integer-coded genetic algorithm, presented in [22], was used to solve the UCP for each of the 24 hour periods, and the LIM was used to obtain the economic dispatch among the committed generators. A potential solution is selected only if all the minimum uptimes/downtimes of the generators (T_i^{up} and T_i^{down}) are satisfied. In order to avoid the local minimum we have applied multiple paths and treat integer problems naturally [23]. The parameters used in the GA application to solve the UCP are given in Table 4.

The minimal cost of the electric power generation amounts to \$543,477 and is found after the application of the UCP and ED. This cost is based on the optimization of a single-objective function. The result of the minimal cost consequently determines the maximal profit (PF_{max}) from the generators.

Table 1. The data for the types, maximal and minimal outputs, and cost function coefficients of generators.

Generator	P_{min} (MW)	P_{max} (MW)	α_i (\$/h)	β_i (\$/MWh)	γ_i (\$/MW^{2}h)
1	150	455	1000	16.19	0.00048
2	150	455	970	17.26	0.00031
3	20	130	700	16.60	0.00200
4	20	130	680	16.50	0.00211
5	25	162	450	19.70	0.00398
6	20	80	370	22.26	0.00712
7	25	85	480	27.74	0.00079
8	10	55	660	25.92	0.00413
9	10	55	665	27.27	0.00222
10	10	55	670	27.79	0.00173

Table 2. The data on environmental impact and other technical data of the generators (**Number of hours in on/off working regime ("+" for the on-state and "–" for the off-state)).

Generator	a_i (tons/h)	b_i (tons/MWh)	c_i (tons/MW^{2}h)	T_i^{up} (hours)
1	103.3908	-2.4444	0.0312	8
2	103.3908	-2.4444	0.0312	8
3	300.3910	-4.0695	0.0509	5
4	300.3910	-4.0695	0.0509	5
5	320.0006	-3.8132	0.0344	6
6	320.0006	-3.8132	0.0344	3
7	330.0056	-3.9023	0.0465	3
8	330.0056	-3.9023	0.0465	1
9	350.0056	-3.9524	0.0465	1
10	360.0012	-3.9864	0.0470	1
T_i^{down} (hours)	hc_i	cc_i	cs_i	**
8	4500	9000	5	8
8	5000	1000	5	8
5	550	1100	4	-5
5	560	1120	4	-5
6	900	1800	4	-6
3	170	340	2	-3
3	260	520	2	-3
1	30	60	0	-1
1	30	60	0	-1
1	30	60	0	-1

The opposite result of the UCP and ED determines the minimal profit (PF_{min}) from the generators (during constant forecast MWh-prices for each hour of a 24-hour period). The calculated values for the minimal and maximal profits are the corner points for

Table 3. Forecast load and a MWh-price

Price ($/MWh)	Load (MW)	Hour
22.15	700	1
22.00	750	2
23.10	850	3
22.65	950	4
23.25	1000	5
22.95	1100	6
22.50	1150	7
22.15	1200	8
22.80	1300	9
29.35	1400	10
30.15	1450	11
31.65	1500	12
24.60	1400	13
24.50	1300	14
22.50	1200	15
22.30	1050	16
22.25	1000	17
22.05	1100	18
22.20	1200	19
22.65	1400	20
23.10	1300	21
22.95	1100	22
22.75	900	23
22.55	800	24

Table 4. The parameters used in the GA applications to solve the UCP.

Number of generations	50
Population size	18
Elimination as a sort of selection (the number of units per one generation)	2
Number of crossover points per one generation	1
Number of mutations per one generation	1
Number of repetitions	10

the fuzzy membership functions of the fuzzy set of the profits from the generators (Fig. 5). These corner points of the fuzzy membership functions can be set up by the owners of the power plants themselves.

The results of the UCP, taking into account only the minimal (EC_{min}) and maximal (EC_{max}) emissions of the CO_2 as the goals of the optimization present the corner points of the fuzzy membership functions presented in Fig. 7. The total costs of the electric power generation, taking into account only minimization and maximization of CO_2 emissions as the optimization goals, amount to \$634,358 and \$637,150, respectively (assuming \$2.5/ton of CO_2).

The optimal operation of ten thermal power plants, where the minimal fuel-based cost of electric power generation is chosen as a single-objective function, is previously calculated, and amounts to \$543,477. The difference between the costs of the power plants operations when only a minimal fuel-based cost and only a minimal CO_2 emission-based cost are considered amounts to \$90,881. That difference is a consequence of asking for the UC, which will enable the minimal CO_2 emission regardless of the fuel-based cost of the electric power generation. It is the value of the opportunity cost which must be taken into account when considering optimality in the operation of thermal power plants.

The corner points of the fuzzy membership function that describe the fuzzy set of a generation capacity reserve (in this case, a spinning reserve) are determined by the system operator. When the fuzzy membership functions of the system attributes and their corner points are determined, the degree-of-optimality based algorithm can be applied as it is given in (8).

First, the $DOs^{attribute}$ are presented for two power system attributes (economy and security), each presented by the sub-attributes of profit and generation capacity reserve, respectively. The costs of a power system operation, based on the economic and security attributes, amounts to \$565,995, which constitutes a 4.1% increase with respect to the electric power generation based only on the minimal fuel and start-up costs. It is expected given the fact that the UCP and ED solutions are based solely on the fuel-based and start-up costs, the other aspects of electric power generation cannot be satisfied, and such an operation cannot be accepted as optimal. Taking into account the determined fuzzy sets of the profits and generation capacity reserve, an average DO^{system} for 24 hours is far from its optimal value and amounts to 0.15.

The DO-based algorithm enables one to select the largest DO^{system} that balances between optimization demands through profits from the generators, generation capacity reserve, and CO_2 emissions in the case study, as well as many other demands, such as maintenance scheduling and the impact of renewable energy sources. However, the DO^{system} (its value being 1 only when the economical attribute with its sub-attribute of minimal fuel-based cost is considered), has fallen to relatively low values from 0.27801 to 0.05961 within 24 hours when the security attribute with its sub-attribute of generation capacity reserve is added to the economy attribute. However, these are the real values of optimality which simultaneously maintain the maximum possible value of the considered security and economy aspects of the operation of a power system.

Table 5 presents the largest DOs^{system} for three considered power system attributes: economy, security, and environment. Each of the attributes are presented with the sub-attributes of profit, generation capacity reserve, and CO_2 emissions, respectively. The cost of electric power generation for a power system operation based on the economy, security, and environment attributes, amounts to \$564,580, which is 3.8% greater with respect to the power system operation based only on its economy attribute. However, as in the previous example where the two system attributes were considered, deviation of the DO^{system} from its value of 1 occurs only when the economy attribute with its sub-attribute of minimal fuel-based cost is considered. The DO^{system} values fall further to lower values, from 0.21290 to 0.01212 within a 24-hour period when all three of the system attributes with their sub-attributes have been taken into consideration. The average value of the DO^{system} for 24 hours is 0.08.

All the cases of electric power generation are based on the different groups of attributes and are characterized with cost that overcomes the cost with respect to the only fuel cost-based optimization of the power generation. However, the costs with respect to the CO_2 emissions, generation capacity reserve, transmission losses, etc. (opportunity costs), which, in the aforementioned literature, are mainly neglected and could not contribute to a real picture of power system operation optimality. Enumerated costs are the opportunity costs because they can be transferred to the benefit-and-earn if they are incorporated into a UCP and ED solution in an appropriate way. The process of searching for a power system optimal operation based on three considered system attributes for the fifth hour of a 24-hour time period is presented in Fig. 8. The largest DO^{system} includes three DOs^{attribute} that determine the aspects of optimality for the three system attributes: economy, security, and environment. These DOs^{attribute} amount to 0.4, 0.7, and 0.63, respectively.

The next largest DO^{system} amounts to 0.068679 and it is the product of three DOs^{attribute} that reflect the economy, security, and environment aspects of system operation optimality. Their respective values are 0.51, 0.44, and 0.31. These values come from the engagement of costly generating units, a decreased value of spinning reserve, and an increased value of CO_2 emissions.

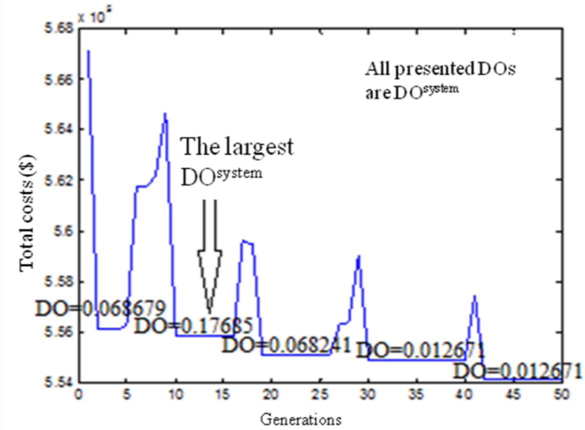

Fig. 8. The DOs^{system} for three considered system's attributes, and for the fifth hour of a 24-hour time period (the analogous diagrams for the 23 other one-hour periods of a 24-hour time duration are not shown).

The picture of optimality of a power system operation obtained in this way is much more apparent. This solution of the UCP and ED balances between the considered system attributes: power demand, the allowable CO_2 emissions, desired profit, and spinning reserve. Other sub-attributes of the system attributes can easily be included into the algorithm such as transmission power losses, generator load angles, renewable energy source uncertainties, and scheduling of storage.

Table 5. The DOs^{system} for each hour of the next 24-hour period of a power system operation based on the economy, security, and environment attributes.

The dispatch of thermal power generators based on DO algorithm which includes three system's attributes (MW)										Fuel-based cost (\$)	Start-up cost (\$)	DO^{system}
455	220	0	0	25	0	0	0	0	0	14.193	900	0.06048
455	270	0	0	25	0	0	0	0	0	15.063	0	0.03133
455	370	0	0	25	0	0	0	0	0	16.809	0	0.03533
455	210	130	130	25	0	0	0	0	0	19.771	1.100	0.21290
455	260	130	130	25	0	0	0	0	0	20.641	0	0.17681
455	360	130	130	25	0	0	0	0	0	22.387	0	0.09671
455	410	130	130	25	0	0	0	0	0	23.261	0	0.05379
455	455	130	130	30	0	0	0	0	0	24.150	0	0.01898
455	455	130	130	110	20	0	0	0	0	26.588	340	0.06783
455	455	130	130	162	43	25	0	0	0	29.365	520	0.03115
455	455	130	130	162	80	25	13	0	0	31.213	60	0.01212
455	455	130	130	162	80	33	55	10	0	32.542	0	0.04255

455	455	130	130	162	43	25	0	0	0	29.365	0	0.04790
455	455	130	130	110	20	0	0	0	0	26.588	0	0.06780
455	440	130	130	25	20	0	0	0	0	24.605	0	0.03190
455	310	130	130	25	0	0	0	0	0	21.513	0	0.14120
455	260	130	130	25	0	0	0	0	0	20.641	0	0.17680
455	335	130	130	25	0	25	0	0	0	23.124	260	0.12056
455	415	130	130	25	20	25	0	0	0	25.341	170	0.05210
455	455	130	130	162	33	25	10	0	0	30.057	60	0.03923
455	455	130	130	85	20	25	0	0	0	27.251	0	0.07840
455	340	130	130	25	20	0	0	0	0	22.855	0	0.12280
455	315	130	0	0	0	0	0	0	0	17.795	0	0.06570
455	215	130	0	0	0	0	0	0	0	16.052	0	0.13859
										561.170	3.410	
										564.580		

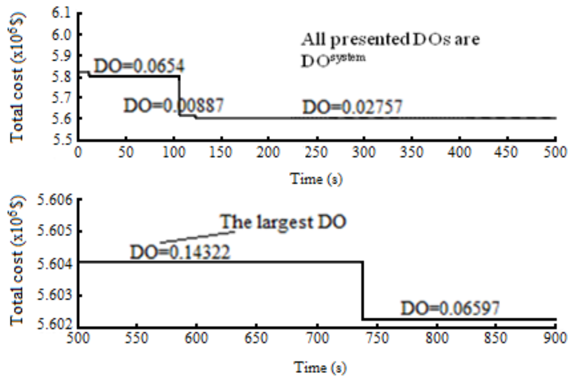

Fig. 9. DO^{system} changes in terms of total cost changes as the objective function in the MILP algorithm.

The calculation is performed by a computer with an Intel Core Duo 1.83 MHz processor with 1 GB of RAM, supported by the GA described in [22] and Mathlab's fuzzy toolbox. The required calculation time is determined by using the algorithm for the UCP and ED solution, which, in this test-case, amounts to 3.7 seconds for a 24-hour time period. It includes the response of the Mathlab's fuzzy toolbox into which the fuzzy membership functions were incorporated. The same calculation is performed by means of the MILP algorithm, which has given the optimal solution in 1.89 seconds. The time difference arises due to the application of different the algorithms. The proposed formulation has been applied to solve a real size case study based on the ten-unit system of [22], which has been replicated ten times so that the case study comprises 100 total units. The load demand has been accordingly multiplied by 10. A spinning reserve requirement of 10% of the load demand has to be met in each of the 24- hour-periods in which the time span is divided. Fig. 9 shows the evolution within the computing time of the best solution found by each MILP formulation presented in [14]. The top figure plots the evolution over the first 500 s, whereas the solutions found within the computing times ranging from 500 to 900 s are depicted in the bottom figure. For each of the total cost changes, the calculated DOs^{system} take into account the same attributes as in the previous case. The optimal solution has been found to have a total cost of $5.604 \cdot 10^6$ \$ with the DO^{system}=0.14322, and not that of $5.6025 \cdot 10^6$ \$ where the DO^{system}=0.06597.

The DO-based algorithm can be applied in all the cases in which there are need to encompass as many factors that influence the attitude of decision-makers as possible. For example, the DO-based algorithm can be applied in the UC problem of hydro-power plants. The water storage or power releases can be considered in the objective function of UC optimization. If the water storage is considered in the objective function, then for each cycle of the optimization (GA or MILP) the power releases are calculated on the basis of the formed fuzzy functions. The usage of water storage is also described by the values of the fuzzy membership function. The product of these fuzzy membership functions determines the DO of the hydro-power plant running in the related time intervals. Moreover, any type of complicated constraints caused by any of the sensitive variables can be efficiently handled via the introduced FMF.

The proposed DO-based algorithm is currently tested for calculation of optimal value of power system hosting capacity [24] in order to realize the maximum penetration of renewable energy sources for which the power system operates satisfactorily.

5. CONCLUSIONS

The UCP and ED solution based on the DOs creates the possibility of choosing between the desired goals. Sometimes, the generators cannot make a large profit because they must avoid excessive CO_2 emissions. However, in some cases, they keep the generation capacity reserve at a desired level, which decreases the profit from the electric power generation to make a profit derived from taking part in the power system security. Moreover, the DO-based algorithm offers several possible optimal solutions which ought to not distort each other, as is the case in the strictly deterministic nature of the Pareto optimal solution. Due to the nature of the fuzzy logic applied to the considered attributes and sub-attributes, the DO-based algorithm can improve some attributes and their sub-attributes through a relocation of the system's resources without endangering other sub-attributes and attributes and without reducing the overall optimality of the system. The new concept of optimality presented in this paper refers to how far the calculated optimal solution, obtained by any type of optimization (mixed-integer linear programming, heuristic approach, etc.), is from a truly optimal solution based on the fuzzy formulation of optimality. The DO-based algorithm can help schedule the system resources on a broad range of its potentiality, thus leading to improved results and more precise performance schedules. The DO-based algorithm can be applied to a large-scale, real-world, and highly complex system where constraints can easily be added and where non-linearity can be captured by fuzzy functions. The presented approach can take into consideration any number of variables and constraints, including binary and non-binary variables.

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