A Multi-Objective Stochastic Approach to Hydroelectric Power Generation Scheduling

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***Abstract*—In this paper, we propose a novel stochastic approach to multi-objective optimization of hydroelectric power generation short-term scheduling. Maximization of profit is chosen as the main objective with additional sub-objective—to reduce the number of startups and shutdowns of generating units. The random nature of future electricity prices and river water inflow is taken into account. We use an artificial neural network-based algorithm to forecast market prices and water inflow. Uncertainty modeling is introduced to represent the stochastic nature of parameters and to solve the short-term optimization problem of profit-based unit commitment. A case study is conducted on a real-world hydropower plant to demonstrate the feasibility of the proposed algorithm by providing the power generation company with the day-ahead bidding strategy under market conditions and a Pareto optimal hourly dispatch schedule of the generating units.**

***Index Terms*-- dynamic programming, hydropower scheduling, multi-objective optimization, stochastic optimization, unit commitment.**

I. INTRODUCTION

Optimization problems of power system operation and short-term scheduling are topical for various stakeholders, including power generation companies, wholesalers and system operators. Depending on the specifics of the interested party, it may have different objectives such as maximization of profit, reliability or social welfare; minimization of production cost, emissions etc. Hydropower scheduling is a large, time-coupled, stochastic, space-coupled and nonlinear optimization problem [1]. Under the conditions of a deregulated electricity market, planning and scheduling becomes even more complex due to many uncertainties involved. Recent challenges have forced a large wave of research targeted to improve the unit commitment (UC) algorithms and tools and tackle the uncertainties by implementing stochastic methods. While there are well-developed traditional applications of stochastic programming to power systems (mostly used for long-term planning), the most promising directions of current studies are focused on the implementation of stochastic approaches for short-term planning within the new environment of decentralized operation, deregulated markets, and competition [2].

Besides that, most of the real-world problems involve several objectives (often conflicting) that need to be considered, thus leading to multi-objective optimization. For example, a generating company interested in maximizing its profit might also want to minimize the amount of emissions (called economic emission load dispatch [3] or economic environmental dispatch [4]) or, in another case, minimize risk and maximize reliability at the same time. In such a case, the solution should be provided as a set of optimal solutions instead of one optimum, because no single solution can be considered to be better than any others with respect to all objective functions [4]. A feasible solution to a multi-objective problem is efficient (also called non-inferior or Pareto optimal) if it is not possible to improve one of the objectives without depraving other ones. The efficient set (also known as Pareto front or trade-off curve) represents the values of the objectives for efficient solutions [5].

One of the most widely used methods for generating efficient solutions is the weighted-sums approach [5], where the trade-off curve is obtained by changing the weight contribution of each single objective to the general objective. The weight factors can be adjusted depending on the importance of each objective [6]. For example, [3] proposes weighted minimax method and employs a stochastic approach (treating uncertainties as random variables) for economic emission load dispatch. In [4], solution for a similar problem in a hydrothermal system is presented by using multi-objective differential evolution Dynamic programming (DP) is employed in [5], but the multi-objective problem is formulated as weighted sum of objectives.

In this paper, we propose a stochastic optimization approach for short-term scheduling of power plant operation from the point of view of a hydro generating company (H-GENCO). Optimal management of the available hydro resources provides a major advantage for the power producer to face the competitiveness [7]. The short-term hydro scheduling solution presented in this paper is validated based on real-world data to serve as decision support for the H-GENCO in developing its bidding strategy for the day-ahead market. In contrast with traditional profit-based optimization, we have included an additional sub-objective, namely, the minimization of the number of startups and shutdowns.

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H-GENCO aims to reduce the number of startups since it involves various costs due to loss of water during startup, wear and tear of equipment (generator windings as well as mechanical equipment), possible malfunctions of the control equipment during the startup and the resulting need of maintenance and loss of water during the maintenance [8]. It is even more important when operating cascade HPPs, since malfunction of control equipment in one of the plants can require rescheduling of the entire cascade and decrease energy production of the cascade.

Minimization of the number of startups is also considered in [9] by employing a two-step genetic algorithm. The first objective considered in [9] is the maximization of hourly plant efficiency according to efficiency curves of each hydro unit.

We assume the market price and water inflow as stochastic variables. To predict the random variables, an artificial neural network (ANN) is used and a "noise" is added for uncertainty representation extracted from historical data.

In a large part of other studies on hydro scheduling, water inflow uncertainty is neglected in the most short-term optimization methods [10]. For example, in [11] it is indicated that water inflows for the next 24 hours can be forecasted with rather good precision, so uncertainty is restricted to electricity market prices. However, it is important to ensure that the water value curves provide a correct picture of the future value of the water at each reservoir because of their direct influence on the shape of the bid curves [12].

This paper is a further development of our research on optimal hydro scheduling part of which has been published previously [13]. In the current paper, we have expanded our study by including an additional criterion of optimization (to minimize the number of startups), thus introducing a two-stage multi-objective approach. In addition to that, we have advanced the optimization algorithm by introducing the last stage of optimal UC and dispatch implemented by means of DP. Solution of the multi-objective problem is provided as a Pareto optimal set, leaving the final choice up to the power plant operator.

The remainder of this paper is organized as follows. The statement of the problem is described in section II where the objective function for the central part of optimization procedure, stochastic nonlinear optimization, is presented. In section III, we introduce uncertainty modeling while section IV describes the optimization algorithm by addressing in more detail the UC and dispatch optimization implemented by means of DP. Section IV presents the case study with results of multi-objective optimization for a real-world HPP. Section V concludes the paper and discusses the future work.

II. Statement of the Problem

A. Main Assumptions

Since our study presents a model to build the generation bids of cascade HPPs, the optimization problem is formulated from the H-GENCO's point of view. We presume that the electricity market is organized according to the day-ahead trading rules as the Elspot market of the Nord Pool (NP) which is also used for the case study. The H-GENCO is assumed to be a price-taker and electricity prices are considered as exogenous variables because the producer under consideration operates only a small part of the pool capacity and cannot influence the market clearing prices.

Another important assumption is that the size of reservoirs under study is relatively small and constraints on the maximum and minimum water levels, both upstream and downstream, need to be considered. Consequently, in a general case the fluctuations of water level affect the effective head available for power production.

Under market conditions, the goal of producer is to maximize its profit, hence it forms the main objective of the problem. At the same time, the H-GENCO aims to reduce the number of startups and shutdowns of generators for cost-effective operation of the HPP. The operation of HPPs must be in strict compliance with the environmental and safety requirements. To take into account the aforementioned goals, we employ multi-objective optimization instead of the traditionally used single-objective optimization.

The profit of the H-GENCO can be expressed as:

$$PF = \sum_{t=1}^{T} \sum_{i=1}^{I} (c_t - om_{\mathrm{v}}) \cdot p_{it} \quad , \tag{1}$$

where c_t—electricity market price at hour t (EUR/MWh); p_{it}—power generation of unit i at hour t (MW); T, t—set and index of hours in the planning horizon; I, i—set and index of generating units; om_{v}—variable production costs. Given that the variable production costs for an HPP are close to zero, we assume them to be negligible and disregard in further calculations.

B. Objective Function

For the particular HPP cascade under study (presented in section V), the objective function for stochastic nonlinear optimization (Fig. 1) of daily bidding strategy is expressed as follows:

$$E[f] = \sum_{n=1}^{3} E[f_n] \to \max \, , \tag{2}$$

where

$$f_n = \sum_{r=1}^{21} \sum_{t=1}^{24} g \cdot \eta_{\mathrm{turb}.n} \cdot \eta_{\mathrm{gen}.n} \cdot H_{n,r,t} \cdot v_{n,t} \cdot c_{r,t} \; ; \tag{3}$$

$$v_{n,t} = S_n \cdot \Delta L_{n,t} / \tau_n \; ; \tag{4}$$

for $n = 1$:

$$H_{n,r,t} = L_{n,r,t}^{\mathrm{up}} - L_{n,r,t}^{\mathrm{down}} - \Delta L_{n,t} + k_n \cdot w_{n,r,t} \; ; \tag{5}$$

for $n = \{2, 3\}$:

$$H_{n,r,t} = L_{n,r,t}^{\mathrm{up}} - L_{n,r,t}^{\mathrm{down}} - \Delta L_{n,t} + k_n \cdot w_n^{\mathrm{lateral}} + b_n \cdot \Delta L_{n-1,t-1} \; ; \tag{6}$$

where:

n index of HPP in the cascade (Fig. 3);

r realization number of price and water discharge forecast (described in more detailed in section III);

t hour;

g acceleration of gravity (9.81 m/s^2);

$\eta_{\text{turb}.n}$ turbine (mechanical) efficiency;

$\eta_{\text{gen}.n}$ generator (electrical) efficiency;

$H_{n,r,t}$ water head (m) at the end of hour t;

$v_{n,t}$ water discharge (m^3/s);

$c_{r,t}$ electricity price (EUR/MWh);

S_n surface area of the reservoir (m^2);

τ_n experimental constant to determine discharge from decrease in reservoir level (s^{-1});

$L^{\text{up}}_{n,r,t}, L^{\text{down}}_{n,r,t}$ water level of upstream and downstream reservoirs at the beginning of hour t (m);

$\Delta L_{n,t}$ change of the water level of upstream reservoir as a result of generation during hour t (m);

$w_{n,r,t}$ water inflow in the reservoir 1 during hour t (m^3/s);

w^{lateral}_n lateral water inflow in reservoirs 2 and 3 (assumed to be constant 6 m^3/s);

k_n coefficient to express increase in water level from inflow $w_{n,r,t}$ (s/m^2);

b_n dimensionless coefficient to express increase in water level of downstream reservoirs from the discharged water through the respective upstream HPP during the previous hour $\Delta L_{n-1,t-1}$.

The variable of optimization is the change of water level of each reservoir, $\Delta L_{n,t}$. The output of optimization provides the H-GENCO with the day-ahead bidding strategy which includes the total hourly power generation and bidding price for the HPP cascade to maximize its profit.

The optimization problem (2)–(6) is subject to several technical, environmental (Table I) and safety constraints, such as the minimum and maximum power generation and ramping rate of the hydro units, minimum and maximum water head of the plant and water level of reservoirs, permissible rate of water level changes, and others [14]. Besides that, allowable operation zones and efficiency curves of the hydro units, which are subject to the power generated, water head and water discharge through the turbines, need to be taken into account.

The power generated by the HPP cascade is nonlinearly dependent on several uncertain random variables (water inflow, water discharge, water head) and, additionally, the profit of H-GENCO is subject to the market price of electricity having a stochastic nature. The formulation of the optimization problem (2)–(6) and uncertainty modeling approach described in the next section allows to properly consider the random nature of the problem with an acceptable computation time.

III. Uncertainty Modeling

This section describes the forecasting of electricity market price and water inflow and the subsequent sampling of numerous forecast realizations $c_{r,t}$ and $w_{n,r,t}$ which are used as input data for the optimization procedure.

It is suggested that the approaches most often used for electricity spot price modeling are statistical time series, computational intelligence models (including ANNs) and hybrid combinations thereof [15]. The same study also concludes that statistical methods for market price prediction perform rather poorly in the presence of spikes, whereas computational intelligence models are flexible and can handle complexity and nonlinearity which makes them promising for short-term predictions. However, the ability to adapt to non-linear, spiky behaviors may not necessarily result in better point forecasts.

ANNs are employed for price forecasting in [14], [16], and [15] contains an overview of using ANNs for electricity price forecasting.

Various models of water inflow are compared in [17] where it is concluded that a dynamic autoregressive ANN model with sigmoid activity function is superior to the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models in forecasting period, especially peak points.

In our study, we employ a three-layer ANN which is trained on historical data of market prices in the Latvian bidding area of NP, water inflow in the River Daugava and ambient temperature. Day of week and hour for which the prediction is performed is also taken into account during the training and forecasting.

Besides that, the algorithm of ANN implies automatic adaptation of some of the ANN parameters before performing each new forecast for the next day. The parameters of ANN are adjusted to suit the best forecast performance the day before.

The output of ANN provides point forecasts of the hourly day-ahead electricity price and water inflow. To take into account uncertainties, we use historical forecast residuals to generate additional realizations of the forecast. By assuming that the forecast errors retain generally the same characteristics in the medium-term, we use the hourly relative errors from the forecasts since 10 days before. Each realization is obtained by adding or subtracting the historical error to the new forecast at the respective hour. In such a way, the 10-day old historical data provides 20 realizations in addition to the one initial point forecast. We assume that all the realizations have equal probabilities. Consequently, for the optimization 21 realizations of electricity market prices, $c_{r,t}$, and water inflow, $w_{n,r,t}$, are used as input data.

This approach allows to model the stochasticity of electricity prices and water inflow while not increasing computational burden too much for a practical application to H-GENCO's daily operation optimization. A more detailed description of the forecasting approach is beyond the scope of this paper.

IV. Optimization Procedure

A. General Algorithm of Optimization

We have decomposed the hydro scheduling problem in several sub-problems (Fig. 1). First, a deterministic linear optimization is carried out for dispatch of the water resources for a 14-day long planning horizon. This step is needed only to obtain the water reservoir level at the end of the first day to be used for the next stage which is stochastic nonlinear optimization (2)–(6). For that, we use the forecasted time series of electricity spot prices and water inflow and employ the Quasi-Newton method of nonlinear programming. As a result, the H-GENCO's bidding strategy for the next day is built based on the profit maximization task and the bids are submitted to the market operator.

As previously stated, the optimization procedure is developed to be used by an H-GENCO operating in the NP power exchange. The market rules require that GENCOs bid their entire generation fleet at once instead of bidding each unit separately. Consequently, the company can decide on its UC schedule after the market has cleared and the amount of power to be sold at each hour is known. Optimal UC and dispatch schedule comprises the next step of the optimization procedure for which we employ deterministic DP (introduced in more detail in the next subsection).

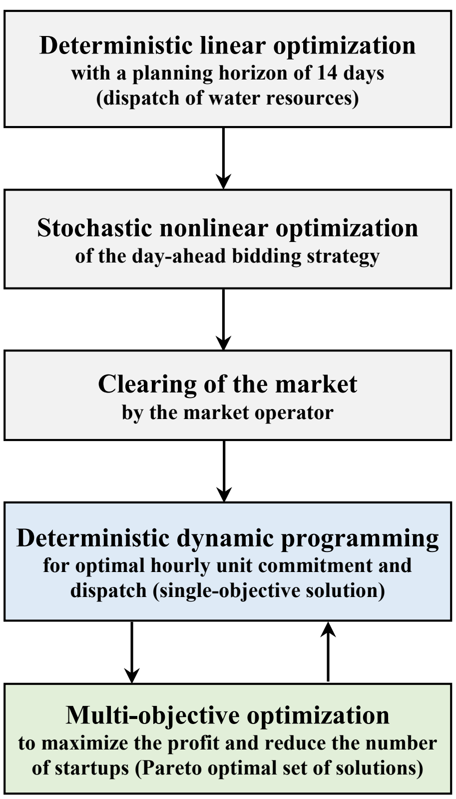


Figure 1. A simplified diagram of the optimization procedure

To assess the objective of minimization of startups, an additional stage of the optimization procedure is introduced. By constraining the minimum operating time of the units to respectively 2 and 3 hours, the dispatch of hydro units is rescheduled retaining the objective of profit maximization. This stage provides the H-GENCO with a set of Pareto optimal solutions according to which the company may choose its operating strategy that maximizes its profit or allows more cost-effective scheduling of the hydro units. Power plant operators try to diminish the number of startups and shutdowns of hydro units because of extra costs involved due to the lost water, wear of equipment, additional maintenance and other factors [8].

B. Optimal Unit Dispatch

After the market is cleared and the hourly amount of power generation for the next day has been determined, it is necessary to establish the optimal dispatch schedule of the HPP generating units.

At this stage, the characteristic of each hydro unit has to be considered. These characteristics illustrate the relationship between effective water head, power and water discharge through the hydro unit. To enable using these relationship curves in calculations, they have to be described mathematically. In this study, we approximate the characteristics by a third-order polynomial such that for every value of water head the water discharge can be expressed as:

$$v_i = a_1 \cdot p_i^3 + a_2 \cdot p_i^2 + a_3 \cdot p_i + a_0 , \tag{7}$$

where v_i —water discharge rate (m^3/s) for unit i, p_i —generator power (MW), and a_0, a_1, a_2, a_3 —polynomial coefficients.

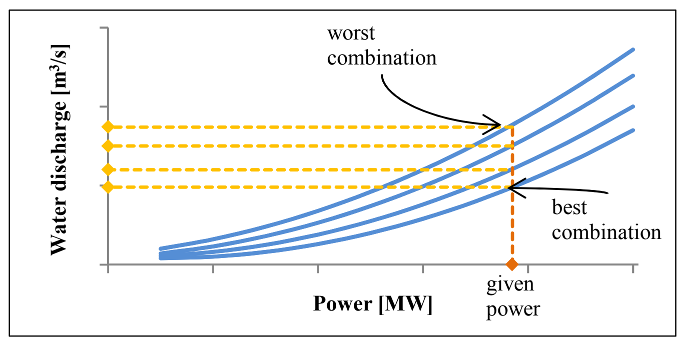


Figure 2. Example of block characteristics of hydro units

As illustrated by curves for several hydro units in Fig. 2, various combinations of turbines require different amount of water to produce the same power.

Evidently, the objective function (8) of the UC sub-task is additive in nature. It provides the option to solve the problem by using DP as opposed to performing exhaustive enumeration.

Traditionally, when DP is applied for optimization of HPP operation, it is done for longer planning horizons and decisions are made at different time stages as, for instance, in [18] and [19]. In this paper, however, we employ DP to solve the hourly UC problem, which is static in time.

There are two ways how to employ DP to find the optimal HPP unit dispatch schedule. If the input variable for each hour is the total amount of water to be discharged through the particular HPP, then DP solves the problem of power generation maximization. On the other hand, if the input variable for each hour is the total power generated by the HPP, water discharge minimization is performed. Both approaches essentially strive to increase the efficiency of operation and thus higher water value, but we have chosen the hourly water discharge as the objective function of DP:

$$v_{t\Sigma} = \sum_{i=1}^{I} v_{it} \;\rightarrow\; \min\,, \tag{8}$$

subject to:

$$\sum_{i=1}^{I} p_{it} \le p_{t\Sigma}\,; \tag{9}$$

$$\underline{p}_i \le p_{it} \le \overline{p}_i \quad \forall t \in T\,, \tag{10}$$

where $\underline{p}_i$ and $\overline{p}_i$ are, respectively, the lower and upper bounds on the power of unit i, $p_{t\Sigma}$ is the total power to be generated in the HPP at hour t. The amount of power generation is normally established after clearing of the market, but for the purposes of this study, we obtain it from the results of the stochastic nonlinear optimization described before. Since at this stage the characteristics of hydro units are modeled with greater accuracy, introducing additional restrictions on their operation, a situation might arise where the amount of power outputted by nonlinear optimization cannot be achieved by any combination of the units within their operational zone, hence (8) cannot be an equality.

For the DP, a recursive equation is formulated to describe the total discharge of the HPP depending on the power of unit i and the units optimized before it:

$$rec_k\left(p\right) = \max\left\{rec_{k-1}\left(p - p_{ik}\right) + v_k\left(p_{ik}\right)\right\}. \tag{11}$$

Recursion is used to obtain intermediate results which are stored in an array with dimensions $k \times I$, where k is the number of steps (value of the constraint (8) divided by the increment between the steps). Once the array is filled, trace-back procedure is initialized starting from the last entry. The optimal trajectory is thereby acquired, which, in this instance, is a vector containing the power generated by each hydro unit.

V. Case Study

A. The Object of Optimization

Plavinas HPP (the second largest HPP in the European Union), which is the first power plant in a cascade of three reservoir HPPs on the River Daugava (Fig. 3), is used for validation of the proposed multi-objective optimization algorithm. Single-objective optimization results for the entire cascade of HPPs have been published in our previous papers, e.g. [13].

Operation of the HPP is subject to several limitations due to the environmental and safety concerns. The constraints imposed by bank erosion, reservoir capacity, integrity of dam facilities and various other factors along with the main technical parameters of the HPP are summarized in Table I. All the constraints are taken into account during the optimization.

TABLE I. Technical Parameters and Environmental Constraints of the Plavinas HPP

Type of Constraint	Value
Installed capacity (MW)	893.5
Surface area of the reservoir (km^2)	35.0
Useful volume of the reservoir (mill. m^3)	143.0
Maximum efficiency (turbine/generator)	0.951/0.977
Permissible upstream level (m)	69–72
Permissible downstream level (m)	30.5–35.9
Maximum discharge (m^3/s)	3030
Permissible hourly decrease in reservoir level (m/h)	0.3
Permissible daily decrease in reservoir level (m/day), depends on the season	0.75–1.5

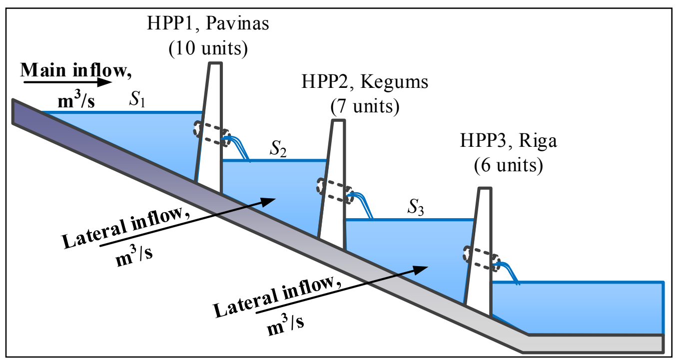
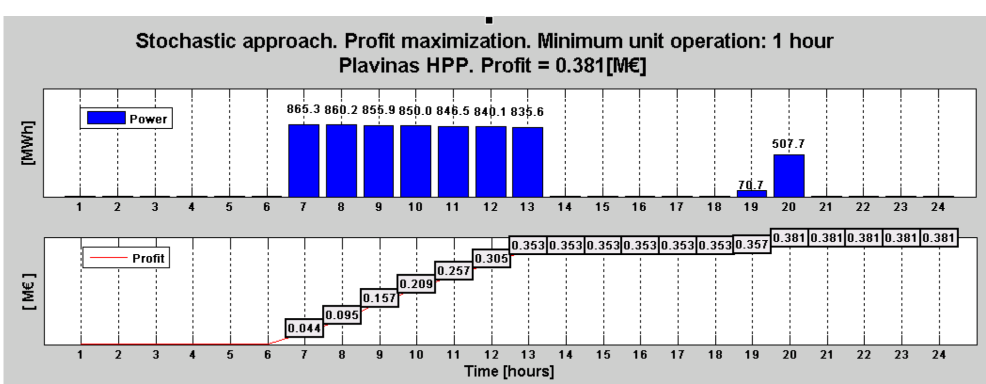


Figure 3. The cascade of HPPs on the River Daugava



Unit number

Hour number	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
7	x	x	x	x	x	x	x	x	x	x
8	x	x	x	x	x	x	x	x	x	x
9	x	x	x	x	x	x	x	x	x	x
10	x	x	x	x	x	x	x	x	x	x
11	x	x	x	x	x	x	x	x	x	x
12	x	x	x	x	x	x	x	x	x	x
13	x	x	x	x	x	x	x	x	x	x
14	-	-	-	-	-	-	-	-	-	-
15	-	-	-	-	-	-	-	-	-	-
16	-	-	-	-	-	-	-	-	-	-
17	-	-	-	-	-	-	-	-	-	-
18	-	-	-	-	-	-	-	-	-	-
19	-	-	x	-	-	-	-	-	-	-
20	-	x	x	-	x	-	x	x	-	x
21	-	-	-	-	-	-	-	-	-	-

Figure 4. Dispatch schedule of the Plavinas HPP with the minimum up time of the hydro units of one hour

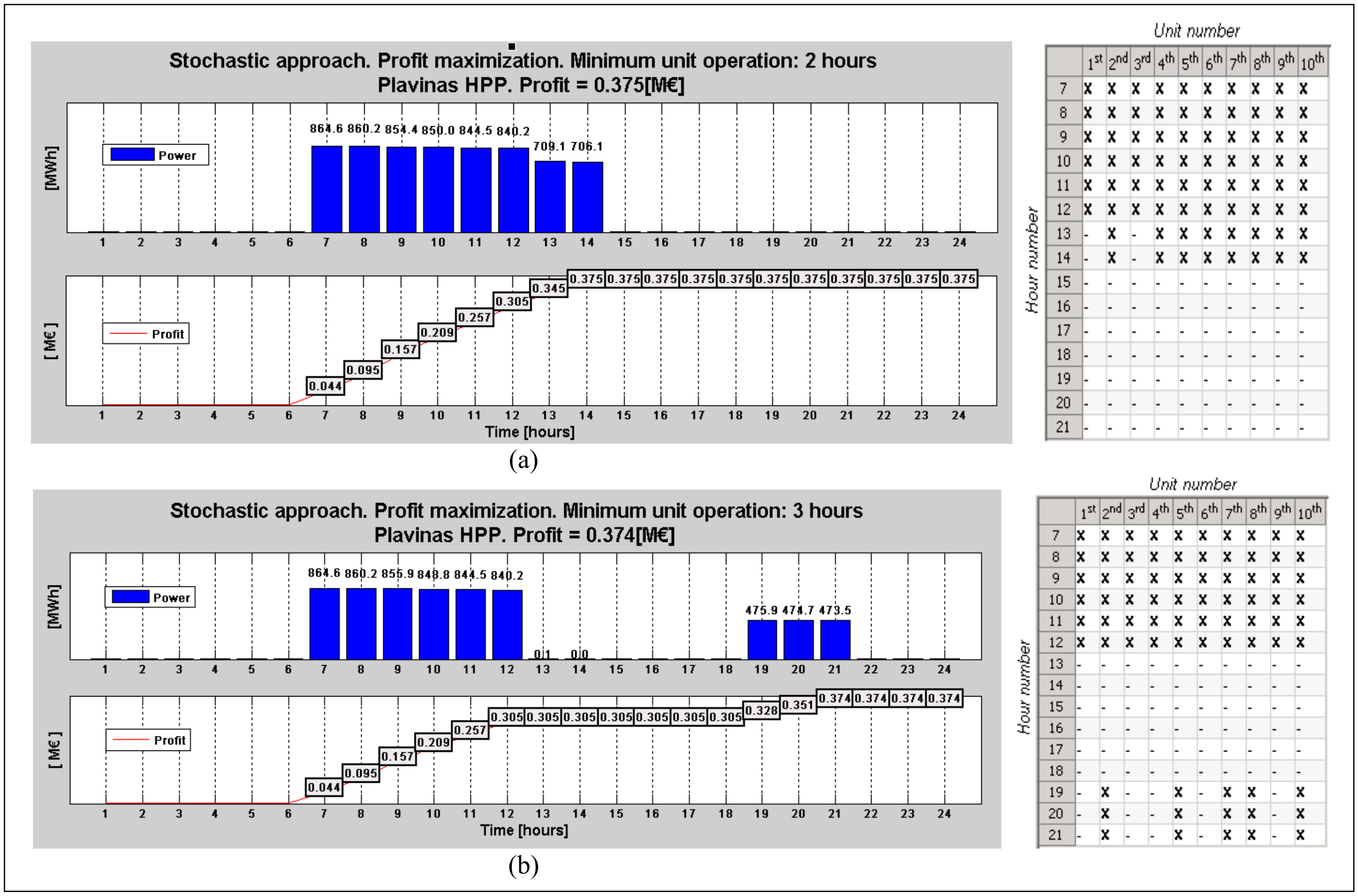


Figure 5. Dispatch schedule of the Plavinas HPP with the minimum up time of the hydro units of (a) two hours and (b) three hours

B. *Results of the Multi-Objective Optimization*

By introducing an additional constraint of minimum up time of units, three dispatch schedules for the Plavinas HPP were obtained with minimum up time of one hour (Fig. 4) and two or three hours (Fig. 5). The charts on the left present the hourly power generation and cumulative profit, while the charts on the right indicate which units are online at each hour (marked by **X**).

The hydro units are operating only a part of the day given the amount of water available. (The Plavinas HPP operates at its full capacity during the annual spring flooding only. During the rest of the year it is scheduled mostly during the peak price period in order to maximize the profit given the limited water resources.)

Comparing all the three dispatch schedules, the maximum difference of the profit is 7000 euros, while the number of startups varies from 10 to 17. The given results allow us to construct a Pareto front (Fig. 6). Points A and B represent the non-dominant solutions and belong to the Pareto front since none of them is better than the other one with respect to both objective functions. However, point C is not on the Pareto front because it is entirely dominated by A in regard to both the profit and the number of startups.

The set of Pareto optimal solutions allows the HPP operator to make the final decision on the operating strategy to maximize its profit by also considering the number of startups.

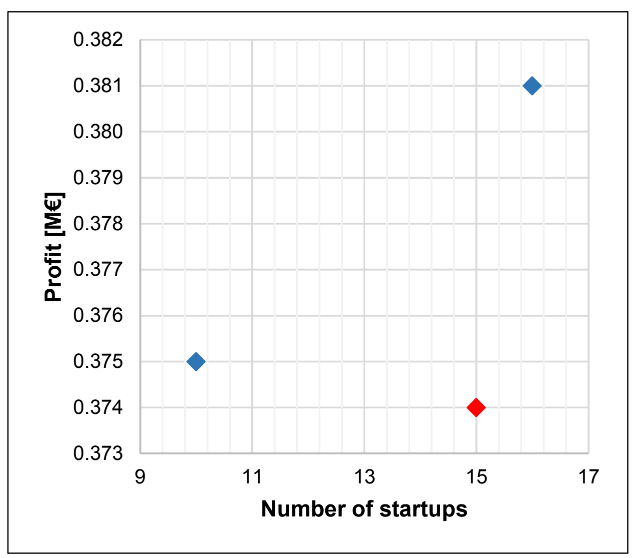


Figure 6. Pareto optimal set of solutions

C. Computational Tools and Resources

All the procedures of forecasting and optimization were carried out in MATLAB R2013a using Optimization Toolbox with solvers for linear and nonlinear programming and Neural Network Toolbox. The Quasi-Newton method was used for nonlinear optimization. A special computing environment has been designed, based on a high-performance multi-processor server with a 12-core processor @ 2.27 GHz, 16 GB of RAM and 64-bit Win Server 2008 operating system. The total computation time of forecasting and optimization procedures varies from 297.7 to 1228 seconds mostly depending on the parameters of the ANN (namely, the number of neurons in the hidden layer which is selected automatically from 10 to 36 neurons during the training stage).

VI. Conclusions and the Future Work

This study presents a practical stochastic approach to optimal profit-based daily and hourly hydro scheduling. The optimization problem addressed herein is a requisite for short-term scheduling of any H-GENCO operating under market conditions. The stochastic nonlinear optimization algorithm employed for building the daily bidding strategy allows to take into account electricity price and water inflow forecast uncertainties while the forecasts are obtained using a self-adaptive ANN. The two-step multi-objective optimization allows the producer to minimize the number of startups of the generating units in addition to the profit maximization. The solution is provided as a Pareto optimal set leaving the final decision up to the power plant operator.

The current study can be extended by including assessment of the cost of startup of the units in the objective function. Besides, the optimization based on the proposed approach will be expanded to incorporate thermal generation of the same GENCO. In that case, a multi-objective problem statement can also be used to maximize the profit of the hydrothermal power generation and, additionally, minimize the number of startups of the units and minimize the emissions from thermal power plants.

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