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The fuzzy model of dynamic production and maintenance planning in pumped-storage hydroelectricity

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Abstract

Developing hydropower plants is a successful strategy for sustainable energy production in countries. On the other hand, due to the high capacity of energy production in the pumping power plant sector, the strategy of saving and continuous exploitation of these power plants is one of the successful policies of governments. Therefore, in this research, the optimization of energy production and maintenance costs in one of the large storage pump power plants in Iran has been discussed and investigated based on the optimization mathematical model strategy. Therefore, a Mixed Integer Nonlinear Programming mathematical model was developed in this field. Due to the uncertainty in the presented mathematical model, the fuzzification strategy was used in the mathematical model. On the other hand, in order to achieve the optimal production plan, an energy production cost optimization policy has been presented to reduce the difference in supply and demand in the energy production network. In order to evaluate the presented mathematical model, four meta-heuristic algorithms of Multi-objective Keshtel Algorithm, Multi-objective Simulated Annealing, Non-dominated Ranking Genetic Algorithm and Non-dominated Sorting Genetic Algorithm II were used with binary coding. The results of this research have shown that the solution of the meta-heuristic NRGA algorithm has been done despite the approximation of the optimal solutions in a suitable period of time, and the results of the research indicate the applicability of the presented model in the studied power plant. Therefore, according to the level of optimization performed in the case study, it has caused the improvement of planning by 7% to 12% and effective optimization processes.

Keywords: production planning, maintenance, pump storage power plant, meta-heuristic algorithm, NSGA-II, NRGA, MOKA, MOSA
2020 MSC: 78M32, 74G65

1 Introduction

Pumped-storage hydroelectricity (PHS) integrate and coordinate storage facilities and controllable loads through an intelligent control center. In addition to being used for marketing the amount of energy produced by distributed generation systems, pumped storage power plants also play an important role in power systems [6]. These power plants

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make it possible to provide system services in the distribution and transmission network, such as work reservation capacity [28]. Storage pump power plants collect electrical output from several scattered energy sources and make this source available to the system operator. If requested, the reserve pump power plants control the immediate dispatch of the connected power plants and thus contribute to the reliability of the network [10]. Gathering Demand Response Plans (DRP) with the aim of providing reserve capacity is a suitable solution to compensate for unforeseen fluctuations in intermittent renewable energy production [2]. Several articles on pumped storage power plants and challenges and Their opportunities have been discussed in the problems of optimal timing or pricing strategy in markets [6, 22, 24, 30, 31, 33]. On the other hand, one of the most important issues that must be considered in the operation of the power system is the balance of production and consumption. This means that at any moment of time, the production rate of the power plants must be equal to the total consumption load and losses of the power network. Otherwise, even if the amount of imbalance is small, the frequency will change and cause many problems in the power network [23]. Based on the predicted load, in an optimization program, the contribution of each of the power plants in providing the load is determined. Storage pump power plants store energy at night or during times of reduced demand for electricity by pumping water from the reservoir lake at the bottom to the lake or reservoir located above and at a higher altitude. When the water passes through the generator turbine units, it is converted into electrical energy. In Figure 1, the general overview of reservoir pumping stations is shown.

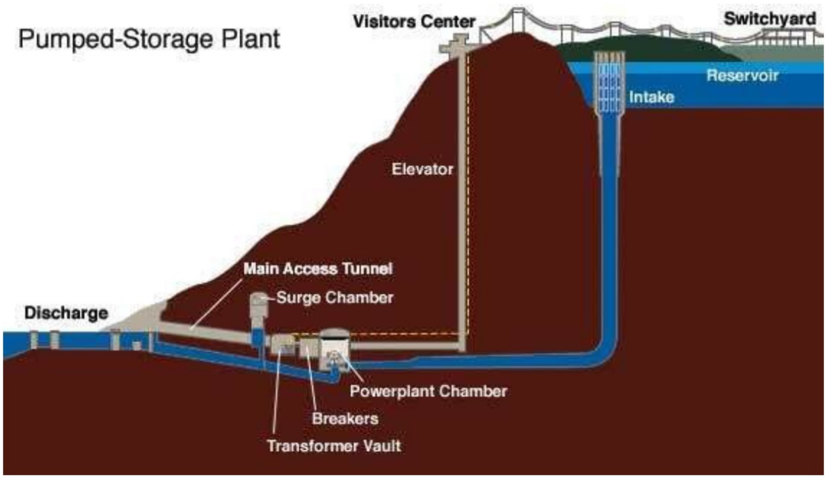


Figure 1: Schematic pumped-storage plant

The main idea is storage surplus generated electricity when off-peak, to usage energy in peak time, in which the demands are more than total capacity [34]. Currently, the efficiency of these power plants is between 70 and 85 percent [13] and has many advantages, including balancing the production and consumption of electricity, energy regulation, provision of side services, optimal operation of other units, sustainability and etc. will be During the past few decades, there have always been many concerns related to the integration of various areas related to production activities in power plants [7]. Each of these areas is like the beating heart of reservoir power plants and should be used in different decisions. Due to the mutual effect of each of these fields, they cannot be examined in isolation and it is very appropriate and reasonable to plan a mechanism that can combine all the important factors as much as possible. commented Many efforts have been made to integrate production planning and maintenance. As it is known, the desired system is connected to each other in the form of a chain, and decision-making in each part shows its effects on other parts [20].

Recent advances in the integration of production and preventive maintenance have connected the issues of economic production quantity and preventive maintenance policies [26], simultaneous control of the rate of production, preventive maintenance [3]. On the other hand, researches that have focused on the integration of production planning and maintenance go back to the years 1970 to 1980. The research in this period was mostly focused on a few vital effects, such as the effect of production complexity and technology, operation speed, commissioning planning and design tolerances considering quality deterioration [21] or the impact of the program. quality inspection planning on the production flow [15] and also some researches focused on the integration of production, quality control and maintenance taking into account the depreciation of the system [5], in fact, a small number of researches published have considered the aspect of production and maintenance together. As it has been stated, the originality of pump power plants is a tank with equipment, that is, the equipment plays a fundamental role, especially in the production of electrical energy and response to demand. Doing work by machines with the passage of time can cause them to be depreciated and the equipment deteriorates more and more (due to the continuous operation of power plant equipment, the rate of deterioration and depreciation of equipment is very high). Therefore, an activity such as maintenance planning should be done to maintain the efficiency and effectiveness of the machines so that the machines continue to work with minimal breakdowns and stops in all periods. Naturally, every piece of equipment can experience some depreciation during the period of time it is checked, one of the effective ways to deal with such a phenomenon is to carry out preventive maintenance. Preventive maintenance or minimal repairs are effective in slowing down the depreciation process [25]. Therefore, it should be done according to the cost considerations and taking into account appropriate schedules to perform preventive maintenance. Therefore, considering the tight competition between production organizations, one of the biggest challenges of these organizations is how to plan the organization to use Resources is to achieve the optimal use of system resources [16]. In fact, it is a successful organization that can use its resources in the best way. Having proper production planning during the planning horizon is a factor that will lead to the optimal use of the organization's resources, including human resources, equipment, financial resources, etc. Therefore, in this research, a new policy is presented in the field of energy production optimization in the pumped power plant based on demand generation policies and the implementation of the maintenance program. The innovations considered in this research can be used for topics related to the use of several energy sources for refilling reservoirs, as well as a demand response planning model and maintenance in the fuzzy uncertainty space by considering the objective function. Minimization of production and maintenance costs will be in the reservoir pump power plant.

2 Literature review

There are different methods to maintain and improve production processes, executive coordination of systems, understanding and practical application of their principles [11]. The results of the research have shown that all approaches to maintenance and improvement of production processes are referred to as "effective action strategies" and all support methods are referred to as "efficient action methods". Increasing production costs and efficiency requirements are constantly faced by manufacturing companies [27]. One of the ways to overcome these challenges is to improve the efficiency and effectiveness of maintenance by developing and integrating predictive maintenance tools and using this information for targeted planning of maintenance actions. Maintenance planning and production planning are two activities that depend on each other, but are often performed independently in production [19]. Maintenance planning affects both the available production time and the probability of failure. This paper presents an integrated decision-making model that coordinates predictive maintenance decisions based on predictive information with scheduling decisions of a machine to minimize the expected total cost [12].

Equipment reliability significantly affects productivity, and to obtain equipment reliability and high productivity, maintenance and production decisions must be made simultaneously to keep the production system healthy [32]. Holding cost, set-up cost, inventory holding cost, shortage cost, production cost and quality cost are analyzed with uncertain demand and product quality assurance due to equipment breakdown. The lowest total cost per unit of time and its specific calculation method are provided. Current manufacturing and production planning systems of manufacturing companies do not include future maintenance strategies that allow for accurate prediction of maintenance tasks [9]. Based on a predictive maintenance strategy, this model constrains actions to minimize general production costs as well as maintenance costs over a planning horizon. The performance of modern manufacturing systems continues to be affected by machine damage and breakdowns [17]. As a result, adequate maintenance programs must be implemented to meet the needs during production stoppages due to unexpected failures or preventive maintenance (PM). Therefore, the online simulated algorithm with a Monte Carlo simulation module is proposed as a solution method. In his research, Kang refers to the integrated control of dynamic maintenance and production in an inefficient production system [14]. This paper presents a dynamic maintenance policy that includes corrective, preventive maintenance and potential opportunities. Maintenance job opportunities use machine breakdowns as potential opportunities to perform maintenance on other machines. Aguirre proposed an approach based on medium-term optimization for the integration of production planning, scheduling and maintenance [1]. The problem presented in this paper is a single-stage multi-stage manufacturing plant with parallel units and limited resources. Liao [18] has generalized the economic production program model by considering maintenance and production in an incomplete process along with the deterioration and depreciation of the production system along with the risk rate. Budjalida stated in his research that production and preventive maintenance work in very important and strategic industries [4]. However, in most real manufacturing workshops, the scheduling of the respective activities is independent and the production constraints cannot be well scheduled. Therefore, we face the problem of scheduling production and maintenance and prevention. In addition, this integration planning at any moment may have errors from the desired theoretical performance when faced with disturbances due to various causes. Therefore, more detailed planning should be sought to develop system reliability. This paper proposes a new approach to investigate the reliability of integrated production and maintenance planning in alternative shift workshops. In his research, Sheikh Alishahi presented a production planning model considering human error and preventive maintenance [29]. The proposed mathematical model includes focusing on conflicting objectives including work error, human error and machine reliability. In order to achieve optimal planning, human errors, maintenance and production factors are considered simultaneously. Human errors are assessed with human error and reducing technique (HEART). Three metaheuristics methods of non-dominated sorting genetic algorithm (NSGA-II), multiple objective particle swarm optimization (MOPSO) advanced algorithm (Pareto II) has presented to find a better solution. Method Taguchi has exerted by setting meta-heuristic algorithm parameters. Several examples and one real case (valuable pieces for vehicles) have demonstrated multi-objective mixed-integer linear programming. The approach proposed may use for similar system problems with minor modifications.

3 Problem definition

In the field research conducted in this research, providing the electricity demand of the subscribers during the hours when the needs of the consumers are the highest (peak consumption hours) is one of the important concerns and issues that the management of the electric network is always involved in. Every year, the amount of demand for electric loads in Iran during the peak hours of consumption is witnessing a remarkable growth compared to the previous years. For example, the average annual peak load during the years 2015 to 2019 is equal to 53041 MW, 55442 MW and 57097 MW, respectively. Examining the annual peaks of the last ten years shows an average annual growth of 8.4 percent of the peak load every year. On the other hand, the peak hours of consumption include a small percentage of the whole time of the year, in order to provide the load, new power plants must be built, which are used only during the peak hours of annual consumption. It can be justified. Pumped-storage power plants are widely used for energy storage. At times when the demand for electricity is low (usually midnight), the additional production of electric power plants is transferred from a lower reservoir to a higher reservoir by pumping water, and the liquid is stored in the upper dam. During the day when the demand increases, the stored energy (in the form of fluid potential difference) is converted into electricity. Therefore, during the process of energy storage and generation, there is about 15 to 30 percent energy loss. Normally, the pumping process has 13.6 percent of energy losses, of which 0.5 percent occurs in transformers, 3 percent in motors, 9.6 percent in pumps, and 0.5 percent in pipes. Also, usually the power generation process has 9.1 percent losses, of which 0.4 percent is in transformers, 1.4 percent in generators, 6.5 percent in turbines, and 0.8 percent in pipes [8]. Pumped-storage power plants have been used in different countries such as China, India, Japan, Europe and the United States of America. In general, pumped-storage power plants are installed in countries that provide a major share of their electric power from nuclear power plants (such as France and Japan) and coal-fired power plants (such as the United States). Therefore, system reliability is very important in these processes. Therefore, in this research, a new mathematical model will be presented in the field of planning energy production in power plant and maintenance of devices and turbines.

3.1 Problem assumptions

- There are two types of products (energy production) in this model: renewable energy production having been transformed fluid to higher elevation reservoir and non-renewable energy having been changed fluid from upper to lower tank to produce electricity.
- The period is limited.
- The pumping station is running parallel.
- Energy generator is inactive in the renewable sector and only active in the non-renewable area.
- The pumping station is inactive in the non-renewable sector and only active in the renewable industry.
- Maintenance operations block only part of the generators' production capacity and pumping station, and the entire system is not out of reach.
- In each period, the number of generators and demand-dependent pumping can increase or decrease.
- All maintenance implementation and production costs have a fuzzy triangular uncertainty.

3.2 Exploratory analysis (Problem modeling)

i Index of type of energy produced (renewable and non-renewable)

t Time period index

j Index of all equipment's power plants

j_1 Index of all fluid pumping equipment from bottom to top

j_2 Index of all generators

3.3 Model parameters

$demand_{it}$ Demand for energy i during the t

$C^1_{ij_1t}$ The cost of energy production i during the t by pumping equipment j_1 in the nominal load

$C^2_{ij_2t}$ The cost of energy production i during the t by the generator j_2 in overload

$C^3_{j_1t}$ Fixed cost of using each pump in the period t by pumping station j_1 in the nominal load

$C^4_{j_1t}$ Fixed cost of using each pump in the period t by pumping station j_1 in the overload

C^5_{it} Fixed cost (production overhead) energy production i during the t

C^6_{ijt} Fixed cost of setting up a pumping station and generator j in energy production i during the t

C^7_{jt} Preventive maintenance costs for pumping station and generator j during the t

C^8_{jt} The energy transfers cost of the pumping station and generator j during the t

C^9_{it} The cost of not responding to energy demand i during the t

C^{10}_{j1t} The cost of pumping failure j1 during the t

C^{11}_{j1t} The cost of using pumping j1 new in the course t

C^{12}_{jt} Rehabilitation cost of pumping station and generator j during the t

IM^{MAX}_{it} Maximum energy production capacity i during the t

S^{MAX}_{it} Maximum energy production deficit i during the t

Sc^{MAX}_{it} Maximum energy production ceiling i during the t in overload

Wp^{MAX}_{t} Maximum number of energy generators available per course t

g_{jt} The number of operation hours' power plant equipment j in energy production period t

A_{jt} The operation percentage of power plant equipment j during the t in overload

U_{jt} Number of power plant equipment j to produce energy in the period t in the nominal load

U^1_{jt} Number of power plant equipment j to produce energy in the period t in overload

e_{ji} Time required to equip the power plant j to produce energy i

M_{jt} Equipment available j to produce energy in the period t

W^{MAX}_{it} Percentage of the maximum energy production deficit i during the t

k^1_{jt} Production capacity percentage of power plant equipment j to produce energy in the period t Which is lost due to preventive maintenance.

k^2_{jt} Production capacity percentage of power plant equipment j to produce energy in the period t Which is lost due to corrective maintenance.

b^1_{jt} Production capacity percentage of power plant equipment j to produce energy in the period t which can be overloaded.

3.4 Decision variable

BN^1_{jit} If equipped j has ability to generate energy i during the t is 1 otherwise 0

X_{jit} Energy production i equipped by j during the t which have transferred nominal load

Y_{jit} Energy production i equipped by j during the t which have transferred to overload

W_{jt} Equipment number j required in the period t

H_{jt} Equipment number j added in period t

J_{jt} Equipment number j out of service in the period t

OT_{jt} Over load operation hours' j during the t

I_{it} Energy production level i during the period t

B_{it} Energy production deficit level i during the period t

PM_{jt} If preventive maintenance for equipment j which have run during the period t 1 otherwise 0

CM_{jt} If corrective maintenance for equipment j which have run during the period t 1 otherwise 0

3.5 Mathematical model

The failure probability density function of energy production equipment is $f(i)_t$ that the cumulative distribution function is $F(i)_t$. the Failure rate of material in each period obtained from equation (3.1) (Based on the collection of information from the studied power plant).

$$r(i)_t = \frac{(i)_t}{1 - F(i)_t} \qquad \forall j, t \tag{3.1}$$

According to the objectives, minimization of rehabilitations has done, and equipment are ready for production, so the failure production equipment's has been evaluated in a non-homogeneous process in the interval (0-t), calculated in equation (3.2).

$$\int_0^t r(i)_t dt \tag{3.2}$$

Therefore, in this policy, maintenance and rehabilitation equipment are determined in what interval the preventive maintenance and rehabilitation will do; consequently, corrective failure will occur accidentally, and all preventive rehabilitation leads to the device will be returned to its previous state. Therefore, the objective of this model is to minimize the cost of production and rehabilitation equipment's, which illustrated in (3.3):

$$\begin{aligned}\min z1 = \sum_i \sum_{j1,j2 \in j} \sum_t C^1_{ij_1t} * X_{jit} + C^2_{ij_2t} * Y_{jit} + C^6_{ijt} * BN^1_{jit} + \sum_j \sum_t C^3_{j_1t} * W_{jt} + C^4_{j_1t} * OT_{jt} \\ + \sum_j \sum_t C^5_{it} * I_{it} * C^8_{jt} + C^9_{it} * B_{it} + \sum_j \sum_t C^{10}_{j1t} * J_{it} + C^{11}_{j1t} * H_{jt} + C^7_{jt}\end{aligned} \tag{3.3}$$

$$\min z2 = C^{12}_{jt} * \int_0^t r(i)_t dt \tag{3.4}$$

According to the non-linear objective function in the second objective function, we have the equation (3.5):

$$\int_0^t r(j)_t dt = \int_0^t \frac{f(j)_t}{1 - F(j)_t} dt = \log\left(\frac{1 - F(j)_0}{1 - F(j)_t}\right) = \log(1 - F(j)_0) - \log(1 - F(j)_t) = -\log(1 - F(j)_t) \tag{3.5}$$

So, the above equation placed in the objective function. Thus, the limitations of the mathematical model are:

$$demand_{it} = \sum_j X_{jit} + Y_{jit} + B_{it} - I_{it} \qquad \forall i, t \tag{3.6}$$

in limitation (3.6), energy demand is the amount of energy produced and transferred in the nominal and overload as well as the amount of energy production and the demand which does not meet in each period. This restriction has shown that the periodic demand program announced has produced either in standard or maximum load; otherwise, the demand does not meet due to the existing problems.

$$I_{it} \le IM^{\max}_{it} \qquad \forall i, t \tag{3.7}$$

The constraint (3.7) has shown the amount of energy produced must be less than the maximum capacity.

$$B_{it} \leq W_{it}^{\max} * S_{it}^{\max} \qquad \forall i, t \tag{3.8}$$

in limitation (3.8), the permissible energy deficit is equal to the percentage of allowable energy deficit announced by energy management staff. The minimum energy deficit coefficient, which declared, each power plant could not produce energy less than the amount load announced by energy management staff.

$$Y_{jit} \leq Sc_{it}^{\max} \qquad \forall i, t \tag{3.9}$$

limitation (3.9) is the amount of energy produced in the overloaded equipment must be less than the maximum available overload.

$$\sum_j W_{jt} \leq Wp_t^{\max} \qquad \forall t \tag{3.10}$$

the Restriction (3.10) ensures that the number of equipment used is less than the maximum available capacity.

$$W_{jt} = W_{jt-1} + H_{jt} - I_{jt} \qquad \forall j, t \tag{3.11}$$

the restriction (3.11) ensures that the number of equipment required during the period is equal to the number of equipment of the previous period and the equipment added and the equipment removed from service.

$$H_{jt} * J_{jt} = 0 \qquad \forall j, t \tag{3.12}$$

restriction (3.12) ensures that in each period, either equipment added or service removed from the system.

$$OT_{jt} \leq g_{jt} * A_{jt} * W_{jt} \qquad \forall j, t \tag{3.13}$$

the restriction (3.13) ensures that the overload working hours' equipment is less than the percentage of maximum overload function.

$$\sum_i U_{jt} * X_{jit} \leq g_{jt} * W_{jt} \qquad \forall j, t \tag{3.14}$$

restriction (3.14) ensures that the working hours of the equipment are less than the nominal load of the equipment.

$$\sum_i U_{jt}^1 * Y_{jit} \leq OT_{jt} \tag{3.15}$$

limitation (3.15) ensures that the energy generation time in the overload is less than the maximum operating time of the equipment in the overload.

$$\sum_i e_{ji} * X_{jit} + (1 - PM_{jt}) * k_{jt}^1 * M_{jt} + (1 - CM_{jt}) * k_{jt}^2 * M_{jt} * \int_{\alpha}^{\alpha+t} r(i)_t dt \leq M_{jt} \qquad \forall j, t \tag{3.16}$$

restriction (3.16) ensures that energy production in the production and capacity lost based on the corrective and preventive maintenance is less than the available size of the equipment.

$$\sum_i e_{ji} * Y_{jit} + (1 - PM_{jt}) * k_{jt}^1 * b_{jt}^1 * M_{jt} + (1 - CM_{jt}) * k_{jt}^2 * b_{jt}^1 * M_{jt} * \int_{\alpha}^{\alpha+t} r(i)_t dt \leq b_{jt}^1 * M_{jt} \qquad \forall j, t \tag{3.17}$$

restriction (3.17) ensures that energy production in the functional overload of the equipment does not exceed the capacity of the devices.

Due to the nonlinearity of constraints (3.16) and (3.17), these two constraints will modify limitations (3.18) and (3.19).

$$\sum_i e_{ji} * X_{jit} + (1 - PM_{jt}) * k_{jt}^1 * M_{jt} + (1 - CM_{jt}) * k_{jt}^2 * M_{jt} * \log(1 - F(j)_\alpha) - \log(1 - F(j)_{\alpha+t}) \leq M_{jt} \qquad \forall j, t \tag{3.18}$$

$$\sum_i e_{ji} * Y_{jit} + (1 - PM_{jt}) * k_{jt}^1 * b_{jt}^1 * M_{jt} + (1 - CM_{jt}) * k_{jt}^2 * b_{jt}^1 * M_{jt} * \log(1 - F(j)_\alpha) - \log(1 - F(j)_{\alpha+t}) \leq b_{jt}^1 * M_{jt} \qquad \forall j, t \tag{3.19}$$

3.6 D-fuzzy the values of the model parameters

Due to the computational complexity, a shift in an object has occurred. Most researchers, the fuzzy computations related to the MCDM technique, have limited to the D-fuzzy algorithm. The ideas expert will enter the direct relation matrix in the form of fuzzy. Then this matrix D-fuzzy with CFCS pattern. The definite matrix has selected as the initial matrix, and other steps continue. The steps for this method have mentioned as follows.

The method CFCS includes an algorithm containing five phases:

The Step 1: Normalize values:

To calculating the lowest to the highest interval, the maximum upper bound values from the least low bound has been subtraction.

$$\Phi_{\min}^{\max} = \max u_{ij}^{t} - \min l_{ij}^{t} \tag{3.20}$$

The Step 2: obtaining the upper and lower limits and normalize

Each of the bound subtracted from interval separately.

$$l_{ij}^{n} = \frac{(l_{ij}^{t} - \min l_{ij}^{t})}{\Phi_{\min}^{\max}} \tag{3.21}$$

$$m_{ij}^{n} = \frac{(m_{ij}^{t} - \min l_{ij}^{t})}{\Phi_{\min}^{\max}} \tag{3.22}$$

$$u_{ij}^{n} = \frac{(u_{ij}^{t} - \min l_{ij}^{t})}{\Phi_{\min}^{\max}} \tag{3.23}$$

The step 3: calculating the normal value upper and lower bound

$$l_{ij}^{s} = \frac{m_{ij}^{n}}{(1 + u_{ij}^{n} - m_{ij}^{n})} \tag{3.24}$$

$$u_{ij}^{s} = \frac{u_{ij}^{n}}{(1 + u_{ij}^{n} - m_{ij}^{n})} \tag{3.25}$$

The step 4: calculate the total definite values normalized

$$x_{ij} = \frac{[l_{ij}^{s} * (1 - l_{ij}^{s}) + u_{ij}^{s} * u_{ij}^{s}]}{[1 - l_{ij}^{s} + u_{ij}^{s}]} \tag{3.26}$$

The Step 5: calculate definite values

$$Z_{ij} = \min l_{ij}^{n} + (x_{ij} * \Phi_{\min}^{\max}) \tag{3.27}$$

4 Research results

According to the mathematical model performed in the previous section, in this section, the research findings will examine. Therefore, in the first section, the research parameters are presented, then the probability density function is discussed, and then defuzzification of the parameters introduced and analyzed in research variables. Since the case study is an NP_HARD problem, a genetic metaheuristic algorithm has used to evaluate and solve the problem model, which will answer after introducing the problem parameters. Introducing mathematical model parameters: The problem indexes introduced to evaluate the mathematical model. According to the Pumped-storage hydroelectricity (PSH) studied in this research, the type of production energy classified into four categories (i=4), wind energy, solar energy, electric energy, and fossil energy. power plant equipment's are classified into three section (j=3) Section 1 Section 2 Section 3. Also, the case study has planned for four periods (t=4). The energy demand required regional power plants has generated by power plants introduced in table 1.

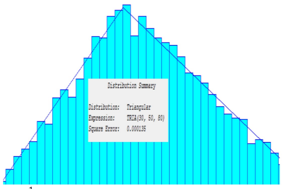
The costs of using the equipment are as follows. As mentioned, the fuzzy triangular function has applied for the usage costs of equipment.

Figure 2 illustrates the maximum capacity production, energy production, energy deficit, and the maximum percentage of Energy production deficit in various periods.

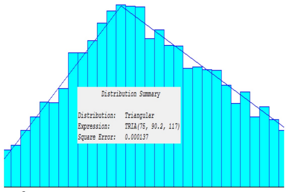
Table 1: Regional electricity demand announced for production in each period (kw/h)

$demand_{it}$	**T=1**	**T=2**	**T=3**	**T=4**
I=1	652000	654000	666000	668000
I=2	652000	667000	667000	668000
I=3	653000	668000	673000	688000
I=4	635000	640000	640000	645000

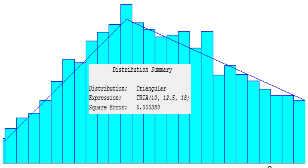
Table 2: Fuzzy costs of using power plant equipment($)



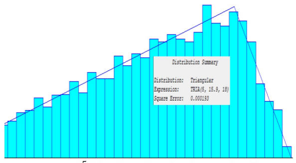
$C^1_{ij_1t}$ The cost of energy production i during the t by pumping equipment j1 in the nominal load



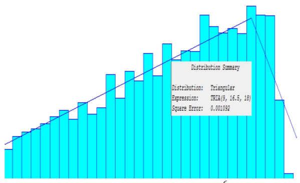
$C^2_{ij_2t}$ The cost of energy production i during the t by the generator j2 in overload



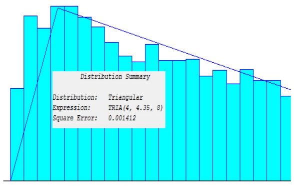
by in the period t Fixed cost of using each pump $C^3_{j_1t}$ in the nominal load j1 pumping station



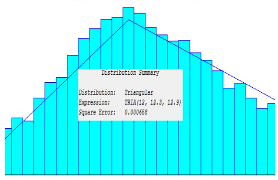
C^5_{it} Fixed cost (production overhead) energy production i during the t



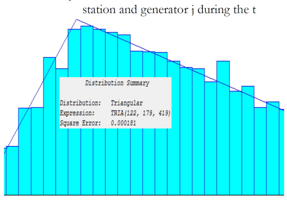
Fixed cost of setting up a pumping station C^6_{ijt} t during the energy production i in j and generator



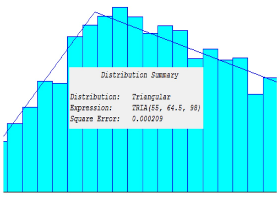
C^7_{jt} Preventive maintenance costs for pumping station and generator j during the t



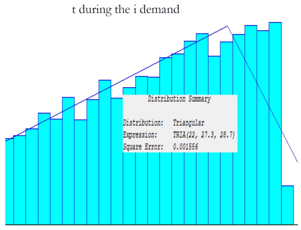
C^8_{jt} The energy transfers cost of the pumping station and generator j during the t



The cost of not responding to energy C^9_{it} t during the i demand



C^{10}_{j1t} The cost of pumping failure j1 during the t



C^{12}_{jt} Rehabilitation cost of pumping station and generator j during the t

4.1 Encoding and decoding strategy

There are a number of developed strategies in order to encode the solutions in various formulations. These strategies are ranging from Michalewicz matrix, Prufer numbers, and priority-based method. In this study, the application of and priority-based method has taken into account and small-sized example is utilized to illustrate the considered chromosome. This method is also leading to satisfying all the considered constraints.

4.2 Tuning the parameters of the algorithms and achieved results

In this subsection, the application of Taguchi approach is employed to set the algorithms' parameters in order to get the optimum results. Using Taguchi approach would decrease the number of total experiments by eliminating unnecessary ones. In this regard, it uses cluster of factors which are based on orthogonal arrays. These factors are

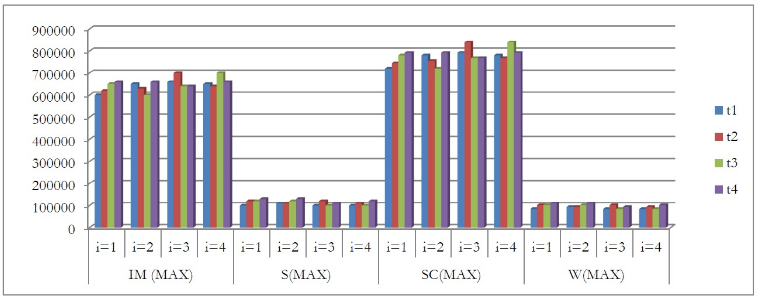


Figure 2: Energy production parameters and energy deficit generated from different parts of the power plant

categorized into two essential groups namely control and noise factor. Hence, to evaluate this response variation, a method is needed to verify signal to noise ratio. It should be noted that, the Taguchi setting is related to the type of response. In this study, the response type of “the smaller is better” is exerted to designate the best settings in each considered levels of proposed metaheuristics.

The initial step to implement the Taguchi experimental design is to identify levels for each factor of the algorithm. The next step would be using Minitab software to analyses the experiment with its Taguchi experiment toolbar. In this respect, the L_9 design was used for NSGA-II, NRGA, and MOSA while the L_{27} design was used for the MOKA algorithm. As aforementioned, to identify the best levels for each algorithm, the evaluation of signal to noise ratio is required. Equation (4.1) represents the selected signal to noise ratio and its evaluation method. This quantity identifies the variation in response relative to the target value and under various noise conditions.

$$Signal/Noise = -10\log(\sum(Y^2)/n) \tag{4.1}$$

where Y and n are the response time and number of orthogonal arrays respectively.

4.3 Metrics for comparing algorithms

In this section, several different criteria are used to check the applicability of the proposed methods. The reason for choosing these metrics is that they measure different aspects of each proposed algorithm. These criteria are:

a) Number of Pareto Solutions (NPS): This criterion is equal to the number of output solutions each time the algorithm is executed. It is obvious that the more Pareto solutions of a method, the more desirable that method is.

b) Mean Ideal Distance (MID): This metric calculates the distance among Pareto solutions and the ideal solution. The formulation of MID can be described as Equation (4.2) for two objective function model.

$$MID = \frac{\sum_{i=1}^{n}\sqrt{\left(\frac{f_i^1 - f_{best}^1}{f1_{total}^{\max} - f1_{total}^{\min}}\right)^2 + \left(\frac{f_i^2 - f_{best}^2}{f2_{total}^{\max} - f2_{total}^{\min}}\right)^2}}{n} \tag{4.2}$$

in this equation, n, f_i^1, and f_i^2 are the number of non-dominated answers and the value of i^{th} non-dominated answers for the two objectives, respectively. The ideal points and the smallest and the biggest values between all non-dominated answers are represented by $f_{best}^1, f_{best}^2, fj_{total}^{\max}$, and $fj_{total}^{\min}$, respectively. The less the value of MID the better performance the algorithm has.

c) CPU time: Calculation CPU time or computational time is among the most regarding methods to investigate the performance of different algorithms. This value determines how fast an algorithm can reach its optimum values that is highly useful in more complex problems which the running time is very important.

d) Maximum Scattering Measure (MS):

$$MS = \sqrt{\sum_{i=1}^{I}(\min f_i - \max f_i)^2} \tag{4.3}$$

e) spread of non-dominated solutions (SNS): This index is presented to identify the dispersion and diversity of the obtained Pareto solutions.

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(MID - C_i)^2}{n-1}} \tag{4.4}$$

4.4 Results of design experiments

Taguchi's method reduces the parameter setting time by reducing the number of trials. First, specify the parameters that are set in each algorithm, and then, using the Minitab software, provide the levels of parameters and orthogonal arrays for the tests, and after determining the number of tests for each algorithm, test the algorithms with the specified levels and ten we ran loads and averaged the results from these ten tests, then unweighted them and obtained S/N plots and obtained better parameters. First, it is necessary to obtain and mention the levels of each algorithm. For this purpose, related articles were studied and candidate levels were identified from them, as described in the table below.

Table 3: Setting the parameters of the algorithms

Algorithm	**Algorithm parameters**	**Parameter level**		
		Level 1	Level 2	Level 3
NSGA-II	Pc	0.75	0.88	0.92
	Pm	0.15	0.22	0.27
	N-pop	150	200	250
	Max-iteration	$4*(I+j+t)$	$6*(i+j+t)$	$8*(i+j+t)$
NRGA	Pc	0.75	0.88	0.92
	Pm	0.15	0.22	0.27
	N-pop	150	200	250
	Max-iteration	$4*(I+j+t)$	$6*(i+j+t)$	$8*(i+j+t)$
MOSA	T0	40	50	60
	α	0.91	0.95	0.98
	Max-iteration	$8*(I+j+t)$	$12*(i+j+t)$	$14*(i+j+t)$
MOKA	M1	15%	20%	25%
	M2	25%	30%	40%
	Smax	15	25	30
	N-Keshtel	100	150	200
	Max-iteration	$4*(I+j+t)$	$6*(i+j+t)$	$8*(i+j+t)$

Finally, with the help of minitab 16 software, experiments have been designed and L9 orthogonal arrays were selected for NSGA-II, NRGA and MOSA algorithms; But for the MOKA algorithm, L27 orthogonal arrays were considered. After running the algorithms for each of the mentioned tests, the response values for the Taguchi method were obtained. These values and orthogonal arrays are presented in the following tables.

Finally, after drawing the signal-noise diagrams of each algorithm, the best values of the parameters can be identified. These values are presented in the graphs below.

4.5 Results of numerical problems

After designing the experiment and setting the parameters, now the appropriate parameters in each algorithm have been specified and it is time to run the algorithms for the generated problems and compare them. As a result, 12 problems are implemented with 4 algorithms. After solving the proposed mathematical model using the mentioned methods, finally the following table shows the results for the problem.

Considering that in this issue we have five standard indicators including: NPS, MS, SNS, MID and CPU time and also there are four options of algorithms including: MOKA, NSGA-II, NRGA and MOSA, it is difficult to determine the best method. Therefore, by using multi-criteria methods, we choose the best method in different dimensions; which is used to obtain the weights of the criteria (indices) from the AHP method and to sort the options (algorithms) from the VIKOR method. In order to obtain the weights of the criteria, first, pairwise comparisons are performed according to the table below. After normalization and calculating the inconsistency rate, the final weight of the criteria is calculated. These mentioned values are presented in the next table.

Table 4: L27 orthogonal array and computational results for MOKA algorithm

test	M1	M2	Smax	N-Keshtel	Max-iteration	MOKA Response
1	1	1	1	1	1	1.14E-05
2	1	1	1	1	2	8.08E-06
3	1	1	1	1	3	1.23E-05
4	1	2	2	2	1	8.14E-06
5	1	2	2	2	2	8.25E-06
6	1	2	2	2	3	1.39E-05
7	1	3	3	3	1	5.45E-06
8	1	3	3	3	2	1.17E-05
9	1	3	3	3	3	4.68E-06
10	2	1	2	3	1	6.44E-06
11	2	1	2	3	2	1.93E-05
12	2	1	2	3	3	7.53E-06
13	2	2	3	1	1	1E-05
14	2	2	3	1	2	3.49E-05
15	2	2	3	1	3	9.76E-06
16	2	3	1	3	1	7.4E-06
17	2	3	1	2	2	1.13E-05
18	2	3	1	2	3	4.9E-06
19	3	1	3	2	1	6.51E-06
20	3	1	3	2	2	2.16E-05
21	3	1	3	2	3	4.76E-06
22	3	2	1	3	1	2.05E-05
23	3	2	1	3	2	3.6E-06
24	3	2	1	3	3	2.11E-05
25	3	3	2	1	1	3.19E-05
26	3	3	2	1	2	8.38E-06
27	3	3	2	1	3	1.55E-05

Table 5: L9 orthogonal array and computational results for NSGA-II and NRGA algorithms

test	Pc	Pm	N-pop	Max-iteration	NRGA Response	NSGA-II Response
1	1	1	1	1	6.72E-06	8.13E-06
2	1	2	2	2	1.84E-05	1.26E-05
3	1	3	3	3	1.49E-05	5.79E-06
4	2	1	2	3	6.17E-06	1.22E-05
5	2	2	3	1	9.99E-06	1.25E-05
6	2	3	1	2	1.52E-05	2.52E-05
7	3	1	3	2	9.44E-06	4.54E-06
8	3	2	1	3	8.24E-06	5.45E-06
9	3	3	2	1	1.53E-05	1.53E-05

Table 6: L9 orthogonal array and computational results for MOSA algorithm

test	T0	α	Max-iteration	MOSA Response
1	1	1	1	1.51E-05
2	1	2	2	1.82E-05
3	1	3	3	2.46E-05
4	2	1	2	1.26E-05
5	2	2	3	3.1E-05
6	2	3	1	2.04E-05
7	3	1	3	6.49E-06
8	3	2	1	1.43E-05
9	3	3	2	1.66E-05

Now it's time to implement the VIKOR method to choose the best option. For this purpose, we consider problems 1 to 4 as small dimension problems, problems 5 to 8 as medium dimension problems and problems 9 to 12 as large dimension problems. Then we take the median of each dimension for each option relative to the criteria and these results will be used as inputs to the Vicor method. These values are presented in the table below.

Finally, after the implementation of Vicor method, the values of the normalized matrix, the normalized weighted matrix, the values of R, S and Q along with the classification of algorithms are presented in the following tables. As received:

Table 7: Computational results of algorithms for 12 subproblems, part l

problem	NPS				CPU Time				MID			
	NSGA-II	NRGA	MOSA	MOKA	NSGA-II	NRGA	MOSA	MOKA	NSGA-II	NRGA	MOSA	MOKA
1	16	10	8	17	98.1	58.4	1540.9	5358.5	2298.9	12678.4	8990.1	17817.7
2	17	12	1	15	171.6	129.4	4219.9	28312.2	4723.2	33355.8	10990.3	39197.5
3	17	16	11	12	372.3	220.8	9678.5	90243.9	20465.5	182899.5	43755.4	534215.7
4	11	17	8	17	586	342.9	16464.7	215506.5	59470.8	455712.2	326958.6	1059624
5	14	12	13	15	1029.9	835.6	36780.8	1417215	135942.1	3701769	437016.2	13655088
6	13	17	13	16	1496.5	1071.5	38512.4	2026231	186517.5	5683377	938598.2	18914851
7	9	10	10	17	1451.1	1289.9	62413.2	2856213	312982.6	15537518	1508550	65972305
8	12	17	8	15	2423.3	2179.4	164712.7	10239191	967841.4	57963043	4815500	310000000
9	14	21	10	16	8673.7	4215.4	783896.8	36226808	3797044	148000000	19515293	993000000
10	21	23	16	14	7164.7	4704.4	703949.2	47964842	2790036	178000000	16303303	1.83E+09
11	15	23	15	17	11468.5	8592.3	1230565	137000000	7171244	557000000	58992096	2.74E+09
12	23	16	13	17	20897.5	12803.9	2874044	247000000	13996885	1.58E+09	112000000	8.81E+09

Table 8: Computational results of algorithms for 12 subproblems, part II

problem	MS				SNS			
	NSGA-II	NRGA	MOSA	MOKA	NSGA-II	NRGA	MOSA	MOKA
1	625762.3	367835.1	1.25E+11	1.32E+11	3.15E+16	3.21E+16	1.15E+21	9.02E+21
2	9106370	659895.2	3.38E+11	4.15E+11	2.22E+18	3.1E+18	1.55E+23	1.99E+23
3	1443909	711843.7	7.75E+11	5.16E+11	6.95E+17	4.9E+17	7.58E+23	4.84E+23
4	1058429	785784.5	6.47E+11	4.79E+11	9.28E+17	6.32E+17	1.58E+23	7.25E+23
5	1102455	1525546	9.47E+11	9.45E+11	1.88E+18	2.14E+18	4.44E+23	4.14E+24
6	1498945	1545794	1.18E+12	2.69E+12	2.93E+18	6.95E+18	7.94E+23	1.79E+25
7	1100258	1129751	1.08E+12	1.19E+12	3.09E+18	3.53E+18	9.96E+23	9.88E+24
8	1197171	1129798	1.13E+12	1.3E+12	3.97E+18	4.84E+18	1.58E+24	1.77E+25
9	2072640.00	1855450	2.94E+12	1.65E+12	1.58E+19	9.08E+18	9.23E+24	4.45E+26
10	3421207	2248624	4.89E+12	3.34E+12	2.68E+19	1.87E+19	1.66E+25	1.03E+26
11	2024875	2302254	1.99E+12	4.58E+12	1.21E+19	2.79E+19	7.5E+23	1.62E+26
12	2661957	1457076	4.53E+12	2.07E+12	2.83E+19	1.3E+19	1.93E+25	7.73E+25

Table 9: The matrix of pairwise comparisons of criteria relative to each other

	NPS	**CPU time**	**MID**	**MS**	**SNS**
NPS	1	3	0.5	0.5	2
CPU time	0.33	1	0.2	0.33	0.2
MID	2	5	1	2	2
MS	2	3	0.5	1	2
SNS	0.5	5	0.5	0.5	1

Table 10: Normalized pairwise comparison matrix with final weight and inconsistency rate (CR=0.05)

	NPS	**CPU time**	**MID**	**MS**	**SNS**	**weight**
NPS	0.213269	0.1765	0.224697	0.135886	0.340221	0.16754
CPU time	0.87497	0.0588	0.080584	0.080681	0.03004	0.051864
MID	0.537633	0.2941	0.569539	0.597745	0.436018	0.374083
MS	0.622043	0.1765	0.300402	0.271654	0.361252	0.266056
SNS	0.099837	0.2941	0.20369	0.149469	0.167193	0.140458

In small dimensions, NSGA-II was chosen as the best option, followed by NRGA, MOKA and MOSA algorithms.

In medium dimensions, NRGA was chosen as the best option, followed by MOKA, MOSA and NSGA-II algorithms.

In large dimensions, NRGA was chosen as the best option, followed by NSGA-II, MOSA and MOKA algorithms.

According to the evaluation carried out on the four meta-heuristic algorithms NSGA-II, NRGA, MOKA and MOSA developed on the mathematical model, it was shown that the efficiency of the NRGA algorithm is higher than the other three algorithms.

Table 11: The score matrix of the options relative to the criteria

Average issues	**options**	**NPS**	**CPU time**	**MID**	**MS**	**SNS**
Problems 1-4	NSGA-II	11.75	167.7658	2.084	694807.9	810089.7
	NRGA	10.5	187.9235	1.92125	631339.6	814059.9
	MOSA	6.75	23.48733	3.467725	429727.2	964632.4
	MOKA	11.75	335.1305	1.95765	581085.6	764987.5
Problems 5-8	NSGA-II	9.5	1207.475	4.4435	879982	2710170
	NRGA	11	1344.163	4.129425	1332722	2887316
	MOSA	7.5	46.41703	4.510575	893257	3065857
	MOKA	12.25	2622.846	4.1518	1139881	2744901
Problems 9-12	NSGA-II	14	7644.613	4.876225	1716750	5797311
	NRGA	17.75	7579.017	4.55705	1966076	5877359
	MOSA	9.75	108.3541	6.808775	1383045	6263086
	MOKA	11.75	13515.47	6.87805	1444900	5538413

Table 12: Results of the VIKOR method for problems with small dimensions

	Normal decision matrix					**Balanced normal decision matrix**					**Selection indicators**			
	NPS	CPU time	MID	MS	SNS	NPS	CPU time	MID	MS	SNS	R	S	Q	rank
NSGA-II	0.58473668	0.4131629	0.44098288	0.6065583	0.49765704	0.10838416	0.0243037	0.1540958	0.14716666	0.08159838	0.13123998	0.19732536	0.00744624	1
NRGA	0.52247784	0.4628045	0.40654402	0.55112518	0.5000357	0.09680112	0.02719946	0.14199566	0.13372206	0.08190864	0.12782712	0.2678578	0.06008702	2
MOSA	0.33590816	0.05781178	0.73366148	0.37510434	0.59249318	0.06225884	0.00341286	0.25637818	0.0910096	0.09711138	0.36134948	0.80398708	1.0342	4
MOKA	0.58473668	0.82539502	0.4141971	0.5072751	0.46994048	0.10838416	0.04840056	0.14468458	0.1230698	0.0770479	0.16950538	0.34635358	0.21935382	3

Table 13: Results of the VIKOR method for medium-sized problems

	Normal decision matrix					**Balanced normal decision matrix**					**Selection indicators**			
	NPS	CPU time	MID	MS	SNS	NPS	CPU time	MID	MS	SNS	R	S	Q	rank
NSGA-II	0.48186885	0.39293715	0.5340048	0.4230993	0.4919229	0.08924265	0.02311395	0.18657	0.10271715	0.0806397	0.29840835	0.8584293	0.91719885	4
NRGA	0.55794795	0.437403	0.4962762	0.6407643	0.5240544	0.10333905	0.0257052	0.17340645	0.155475	0.08592585	0.08530395	0.1664619	0	1
MOSA	0.3803955	0.0151329	0.5420895	0.42942195	0.5563932	0.070482	0.00093285	0.18936855	0.1042719	0.091212	0.3621531	0.79841595	0.9915159	3
MOKA	0.62138175	0.8534541	0.4989711	0.54799755	0.4981419	0.11515515	0.05006295	0.1743393	0.13298295	0.0816762	0.15329835	0.34256325	0.25922865	2

Table 14: Results of the VIKOR method for large-dimensional problems

	Normal decision matrix					**Balanced normal decision matrix**					**Selection indicators**			
	NPS	CPU time	MID	MS	SNS	NPS	CPU time	MID	MS	SNS	R	S	Q	rank
NSGA-II	0.5216678	0.4496996	0.4216442	0.53071465	0.5015411	0.09666915	0.026429	0.14729085	0.12879055	0.08223485	0.10703745	0.3832205	0.1967944	2
NRGA	0.66143655	0.4458369	0.3939954	0.60776535	0.5084533	0.1225899	0.02612405	0.1376341	0.14749415	0.083353	0.0886388	0.12187835	0	1
MOSA	0.3632971	0.00640395	0.5887568	0.4275399	0.5417945	0.0672923	0.0004066	0.2057396	0.10378465	0.0888421	0.3445935	0.7796555	0.89502825	3
MOKA	0.43780655	0.7951063	0.59475415	0.4466501	0.4791781	0.0811167	0.04665735	0.2077726	0.1083589	0.07857545	0.3551651	0.94321035	1.0165	4

5 Conclusion

Energy, as a basic component of modern society and life, has a direct impact on every human activity and plays an important role in social and economic development. In fact, energy is deeply involved in every component of human development, such as economic issues. It is socially and ecologically embedded and is an industrial infrastructure and an essential element of daily life. The world population at the end of this century is expected to more than 13.1 billion people and energy consumption around the world has increased with the increase in population and prosperity so that the global energy demand will double and today the fact that energy production and consumption in the concept of sustainable development It is one of the most important goals, it cannot be hidden. To meet the growing energy needs, many countries have turned to renewable energy sources because they are very sensitive to economic, environmental and social factors. Using renewable resources to replace fossil fuels brings sustainability by reducing external dependence. Therefore, in this research, a mathematical model for a pumped storage power plant has been presented with the aim of minimizing the costs of production, maintenances and production scheduling. One of the most important limitations considered in this issue is the working capacity of the pumps and the number of equipments in operation and operating in overload and partial load. Finally, the optimization performed with four meta-heuristic algorithms NSGA-II, NRGA, MOKA and MOSA showed that the performance of NRGA algorithm is better. According to the presented mathematical model, future research proposals are introduced as follows:

1. Considering the deficit cost of energy production in the reservoir pumped power plant as social costs
2. Considering the costs of power plant propulsion energy supply in the mathematical model
3. Considering the uncertainty of stabilization in the mathematical model and analyzing the results obtained with the presented model

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