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Coyote optimization algorithm to solve energy hub economic dispatch problem

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Abstract: Regardless of energy type that we need today, it is important to use it efficiently and economically in the production, transmission and distribution stages. In line with the developing technology and needs, a new energy concept has emerged in which different energy types managed together in the past were managed independently. In this concept, energy infrastructures of more than one energy carrier such as electricity, gas and heat are met as Energy Hub (EH) to supply the demands such as electricity, heating, cooling and compressed air by means of energy conversion, distribution and storage devices. EHs are expected to meet the demands energy with low operating costs. Energy hub economic dispatch problem (EHEDP) is a non-linear, non-convex, uniform and non-differential multidimensional optimization problem. In this study, the energy cost of the system is minimized by using the Coyote Optimization Algorithm (COA) for the solution of the EHEDP. The results obtained with COA have been compared with the results of heuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Moth Swarm Algorithm (MSA) and Symbiotic Organisms Search Algorithm (SOS) in the literature. The compared results showed that COA performed better than other algorithms in solving EHED problem.

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Enerji merkezi ekonomik yük dağıtım problemi çözümü için kır kurdu optimizasyon algoritması

Anahtar Kelimeler
Enerji merkezi
Ekonomik dağıtım
Kır kurdu optimizasyon algoritması

Makale geçmişi:
Geliş Tarihi: 09.01.2020
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Özet: Günümüzde ihtiyacımız olan enerjinin türü ne olursa olsun üretim, iletim, dağıtım aşamasında verimli ve ekonomik olarak kullanımı önemli hale gelmiştir. Gelişen teknoloji ve ihtiyaçlar doğrultusunda, geçmişte birbirinden bağımsız olarak yönetilen farklı enerji türlerinin bir arada yönetildiği yeni bir enerji konsepti ortaya çıkmıştır. Bu konseptte elektrik, gaz ve ısı gibi birden fazla enerji taşıyıcısının, enerji dönüşüm, dağıtım ve depolama cihazları vasıtasıyla, talep edilen elektrik, gaz, ısıtma, soğutma ve basınçlı hava gibi ihtiyaçların karşılanabilmesini sağlayan enerji alt yapıları Enerji Merkezi (EM) olarak kabul edilir. EM' lerinin, talep edilen enerjiyi düşük işletme maliyeti ile karşılaması beklenir. Enerji merkezi ekonomik dağıtım problemi (EMEDP) doğrusal, konveks, düzgün ve diferansiyel olmayan çok boyutlu bir optimizasyon problemidir. Bu çalışmada EMEDP çözümü için Kır Kurdu Optimizasyon Algoritması (KKOA) kullanılarak sistem enerji maliyeti minimize edilmiştir. KKOA ile elde edilen sonuçlar, literatürde yer alan Genetik Algoritma (GA), Parçacık Sürü Optimizasyonu (PSO), Güve Sürüsü Algoritması (GSA) ve Simbiyotik Organizmalar Arama Algoritması (SOAA) gibi sezgisel algoritmaların sonuçları ile karşılaştırılmıştır. Karşılaştırılan sonuçlar, KKOA' nın EMED problemi çözümünde diğer algoritmalara göre daha iyi performans gösterdiğini ortaya koymuştur.

1. Introduction

Nowadays, to providing the energy needs of countries is one of the important problems faced by societies. Due to the rising of energy demand in parallel with the increase in the world population, the need for energy has become more and more important for the sustainable development of countries. When economic,

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social, environmental and security factors are considered together, it is clear that energy is a strategic issue for countries. In addition, due to the limited fossil fuels and their negative impact on the environment, the importance of reliable and sustainable energy has increased. Economic and trouble-free operation of a sustainable energy system is possible by using a combination of suitable energy carriers [1], [2]. The new vision of energy systems is integrated energy network systems called multiple energy carrier networks or hybrid systems, where different types of energy are managed together. In this concept, Energy Hubs (EH) play an important role as networks of different energy types are intersections where the energy flow between each other is controlled [3], [4]. The energy demand of loads The energy demand of the loads is provided by multiple energy carrier networks of different energy types which collected, converted and storaged in EH. An energy center model may include transformers, micro turbines, central air conditioning, compressors and energy storage devices [5]. Besides, the storage devices as thermal storage and electrical batteries are instruments for energy storage in EH. An EH may include one or more different infrastructure devices and renewable energy sources. Large buildings such as power plants, industrial plants, airports, hospitals and cities or towns can be modeled as EH by using these infrastructure devices. Energy flow is from the input energy sources to the output in an energy hub model [1]- [14].

Similar to electric power systems, EH involve different optimization problems. In particular, the most widely known economic power dispatch problem in power systems applies to EH with multiple energy systems. In an energy system, different equality and inequalities must be achieved while providing the demanded energy with minimum energy cost. System status is determined by optimizing fuel cost, emission cost and energy losses via adjusting control variables, state variables and power flow in EH. Since EH contain different energy infrastructures, Energy Hub Economic Dispatch Problem (EHEDP) becomes a non-convex, non-smooth, nonlinear and high dimensional optimization problem [3].

In the literature, there are different studies for modeling EH and operating these models under optimal conditions. In [1], the effect of components that make up the micro EH on the system efficiency is investigated and a method is provided to operate these plants with minimum operating cost. [2] presents the different models that can be used for the EH and suggestions to help create a new model in the literature. On the other hand, meta-heuristic algorithms take part in literature that are used and given successful results for solving large-scale, complex multi-objective EHEDP. In [3], a new optimization algorithm is presented in which the acceleration coefficient of the Gravitational Search Algorithm (GSA) is changed over time to solve the high dimensional EHEDP involving different converters and showed a better convergence with reasonable calculation time compared to other optimization algorithms used for this problem in the literature. The modified firefly algorithm was used in [6] to minimize EH fuel cost and CO2 emissions consequently it was shown to yield better results than conventional mathematical methods. In [7], multi-agent genetic algorithm was applied to online EHEDP of wind energy integrated energy hub system. Multi-agent bargaining learning algorithm is presented in [8] to reach fast a quality optimum solution of the economic dispatch problem of distributed EH and the algorithm had better results than six heuristic optimization algorithms that frequently used in literature.

In this study, energy cost has minimized by using Coyote Optimization Algorithm (COA) for the solution of EHEDP. The proposed algorithm testing process has been implemented by using 7 energy hubs that obtained from the 17 energy generation units. The inputs of tested energy hub model have been selected as electricity, heat and natural gas. Besides, demanded electricity, gas, heat, cooling or compressed air needs are supplied at the EH outputs. The results of algorithm have been compared with GA, PSO, MSA and SOS that are previously used for solving the EMED problem in the literature and the algorithm performance has been shown.

In the following sections of this study, structure and mathematical model of the energy hub model, objective function of the optimization problem to be solved, equality and inequality constraints, structure of COA, the results, discussion and conclusion sections are presented.

2. Material and Method

2.1. Energy hub, main structure and mathematical model

The various types of energy that end users need are provided by infrastructures with different energy carriers. Integration of different energy infrastructures is beneficial in terms of transformation between energy types. Considering parameters such as cost, emission, security of multiple energy carriers and structures are used for energy conversion and transfer, different models and methods are utilized in order to ensure efficiency with optimum connection and power change. EH are the structures in which the transformation, regulation and storage of energies provided from energy networks formed by different energy carriers are realized. An energy hub consumes energy such as electricity, gas, heat that received from the input energy carriers and meets the demands such as electricity, air conditioning and compressed air needed through the output energy carriers. Different units can be used for the conversion, conditioning and storage of energy when designing EH that serve as interfaces between loads and different energy infrastructures [15]. The generals main structure of EH and basic infrastructure devices in which the energy hub models that are used in this article are given in Figure 1.

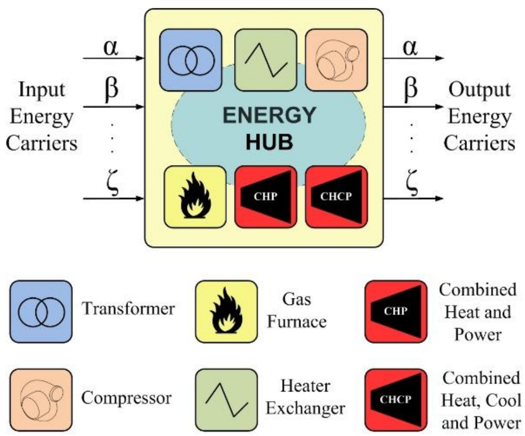


Figure 1. The general main structure of EH and basic infrastructure devices

An energy hub formed as the general model shown in Figure 1. contains three basic elements. These elements are converters, direct connections, and storage devices. The direct connections are used to transferring any energy received from the input energy carriers to output without being converted to another form. Electrical connections and pipelines are example of the direct connections. The converters are devices that can be used by converting the energy to another needed form. Transformer (T), Gas Furnace (GF), Compressor (C), Heat Exchanger (HE), Combined Heat and Power element (CHP), Combined Heat, Cooling and Power element (CHCP) are the basic converter infrastructure devices that can be used in EH.

Energy flow is from the input energy source to the output energy carriers in an EH model. The analysis of energy flows in converter elements of the multi-input and output EH models is carried out with the conversion matrix (C) that provides the correlation between input and output energy vectors. The energies are transferred to the output of energy hub are calculated by the following expression.

$$\begin{bmatrix} E_\alpha^{out} \\ E_\beta^{out} \\ \vdots \\ E_\omega^{out} \end{bmatrix} = \begin{bmatrix} C_{\alpha\alpha} & C_{\beta\alpha} & \cdots & C_{\omega\alpha} \\ C_{\alpha\beta} & C_{\beta\beta} & \cdots & C_{\omega\beta} \\ \vdots & \vdots & \ddots & \vdots \\ C_{\alpha\omega} & C_{\beta\omega} & \cdots & C_{\omega\omega} \end{bmatrix} \begin{bmatrix} E_\alpha^{in} \\ E_\beta^{in} \\ \vdots \\ E_\omega^{in} \end{bmatrix} \tag{1}$$

where α, β, ..., ω are various energy carriers, $\begin{bmatrix} E_\alpha^{out} & E_\beta^{out} & \cdots & E_\omega^{out} \end{bmatrix}^T$ is output energy vector, $\begin{bmatrix} E_\alpha^{in} & E_\beta^{in} & \cdots & E_\omega^{in} \end{bmatrix}^T$ is input energy vector. C is formed by the connection factors of the transformation and transfer devices as $C_{\alpha\alpha}, C_{\beta\alpha}, \dots, C_{\omega\alpha}$ in energy hub. Further, the C is associated with the configuration that determines the design of the energy hub. Each C that constituting the transformation matrix is obtained by multiplying the dispatch factor *(v)* and efficiency of the conversion and transfer devices *(η)* *(C = v. η)* [3], [15].

In this study, 7 different energy hub models that used in [3] and [4] which have formed with six infrastructure devices shown in Figure 1 have used and these hub models given in Figure 2.

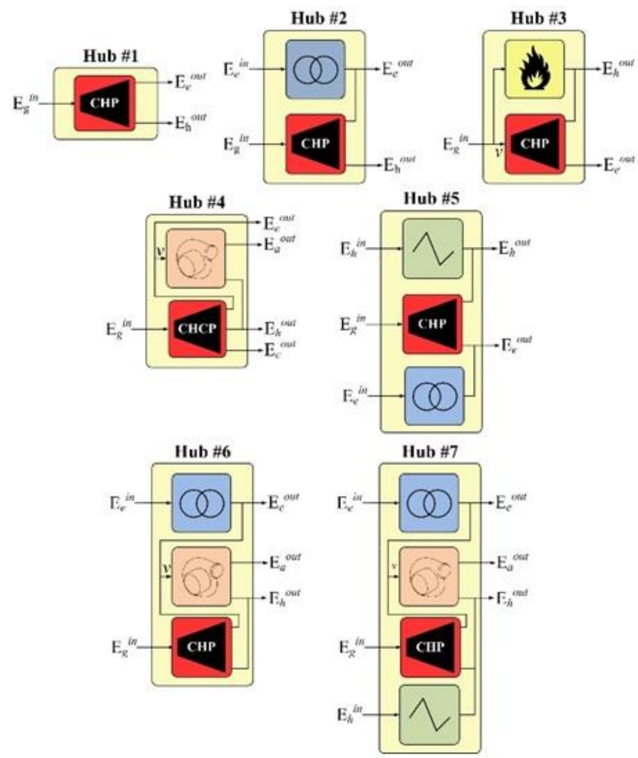


Figure 2. The energy hubs structures used in this work

In the selected hub models, the electricity *(e)*, heat *(h)*, cooling *(c)* and compressed air *(a)* demands of the output energy carriers have supplied by using electricity, natural gas *(g)* and heat energy received from the input energy carriers. The matrix expressions of these energy centers are as follows [3], [4]:

Hub #1: A CHP element has been used in this hub which converts natural gas from the input energy carrier into electrical and heat energy. The correlation between input and output energies is as follows:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \end{bmatrix} = \begin{bmatrix} \eta_{CHP_e} \\ \eta_{CHP_h} \end{bmatrix} E_g^{in} \tag{2}$$

Hub #2: The energy conversion expression of the hub which included T and CHP, are given as following equation:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \end{bmatrix} = \begin{bmatrix} \eta_T & \eta_{CHP_e} \\ 0 & \eta_{CHP_h} \end{bmatrix} \begin{bmatrix} E_e^{in} \\ E_g^{in} \end{bmatrix} \tag{3}$$

where η_T is efficiency of T and η_{CHP_e}, η_{CHP_h} denote electrical and heat efficiency of CHP.

Hub #3: In this hub, natural gas is supplied from the input energy carrier is consumed and electricity and heat energy are produced. The generated energies are calculated as follows.

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \end{bmatrix} = \begin{bmatrix} \nu\eta_{CHP_e} \\ \nu\eta_{CHP_h} + (1-\nu)\eta_{GF} \end{bmatrix} E_g^{in} \tag{4}$$

where η_{GF}, ν are respectively efficiency and dispatch factor of GF.

Hub #4: Electricity, heat, cooling and compressed air demands are met by the C and CHCP in this hub. The correlation of input and output energies are expressed as follows:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \\ E_c^{out} \\ E_a^{out} \end{bmatrix} = \begin{bmatrix} (1-\nu)\eta_{CHCP_e} \\ \eta_{CHCP_h} + \nu\eta_{CHCP_e}\eta_{c_h} \\ \eta_{CHCP_c} \\ \eta_{CHCP_e}\eta_{c_a} \end{bmatrix} E_g^{in} \tag{5}$$

where η_{c_h}, η_{c_a} are respectively heat and air efficiency of C also η_{CHPC_e}, η_{CHCP_h}, η_{CHCP_c} are electricity, heat and air efficiency of CHCP unit.

Hub #5: This hub contains HE, CHP and T units and supply electricity and heat demands. The generated energies can be calculated as follows:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \end{bmatrix} = \begin{bmatrix} \eta_T & \eta_{CHP_e} & 0 \\ 0 & \eta_{CHP_h} & \eta_{HE} \end{bmatrix} \begin{bmatrix} E_e^{in} \\ E_g^{in} \\ E_h^{in} \end{bmatrix} \tag{6}$$

where η_{HE} is efficiency of HE.

Hub #6: Electricity, heat and compressed air demands are met by run out of electricity and natural gas in this hub. The output energies are expressed as:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \\ E_a^{out} \end{bmatrix} = \begin{bmatrix} (1-\nu)\eta_T & (1-\nu)\eta_{CHP_e} \\ \nu\eta_T\eta_{c_h} & \eta_{CHP_h} + \nu\eta_{CHP_e}\eta_{c_h} \\ \nu\eta_T\eta_{c_a} & \nu\eta_{CHP_e}\eta_{c_a} \end{bmatrix} \begin{bmatrix} E_e^{in} \\ E_g^{in} \end{bmatrix} \tag{7}$$

Hub #7: The hub contains HE and infrastructure units used in Hub #6 and its output energies are expressed as:

$$\begin{bmatrix} E_e^{out} \\ E_h^{out} \\ E_a^{out} \end{bmatrix} = \begin{bmatrix} (1-\nu)\eta_T & (1-\nu)\eta_{CHP_e} & 0 \\ \nu\eta_T\eta_{c_h} & \eta_{CHP_h} + \nu\eta_{CHP_e}\eta_{c_h} & \eta_{HE} \\ \nu\eta_T\eta_{c_a} & \nu\eta_{CHP_e}\eta_{c_a} & 0 \end{bmatrix} \begin{bmatrix} E_e^{in} \\ E_g^{in} \\ E_h^{in} \end{bmatrix} \tag{8}$$

2.2. Objective function, equality and inequality constraints

In this study, the objective function that given in equation 9. has been minimized. The objective function is energy cost function for EHED problem solution. Valve point loading effect due to thermal power units that used valves cause a fluctuation of transferred active power to the output. This effect leads to increase in fuel costs as shown in Figure 3. The energy cost function in which valve point loading effect is taken into consideration is expressed as follows [3], [4], [9]:

$$\begin{aligned} OF = EC = & \sum_{i\epsilon\{g,h\}} \sum_{j=1}^{n_i} \left(a_{j,i} + b_{j,i}E_{j,i}^{in} + c_{j,i}\left(E_{j,i}^{in}\right)^2\right) \\ & + \sum_{j=1}^{n_e} \left(a_{j,e} + b_{j,e}E_{j,e}^{in} + c_{j,e}\left(E_{j,e}^{in}\right)^2 \right. \\ & \left. + \left|d_{j,e}\sin\left(e_{j,e}\left(E_{j,e}^{in.min} - E_{j,e}^{in}\right)\right)\right|\right) \end{aligned} \tag{9}$$

where *OF* represents the objective function and *EC* shows the energy cost. $\{a_{j,i}, b_{j,i}, c_{j,i}\}$ represents cost coefficients of the input energy sources and , $e_{j,i}$ and $d_{j,e}$ denote cost coefficients which used for valve point loading effect in Equation 9. Finally, $E_{j,i}^{in}$ represents the energy consumed from the input energy carriers.

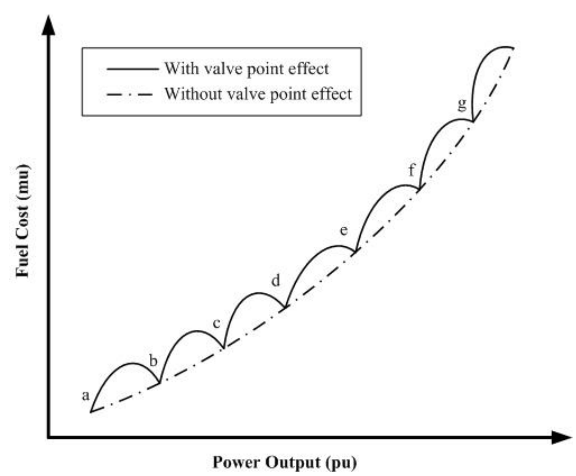


Figure 3. Valve point loading effect

Equality and inequality constraints to be considered when minimizing the optimization problem given above are as follows [3]:

- Energy flow in the energy hubs must be supplied by the Equation 10. for the different energy hubs that build up the system and the equilibrium between the energy output and demand of the hubs should be ensured by the constraint in Equation 11.:

$$Input_i = C_i Output_i, \qquad i = 1, \dots, N_{hub} \tag{10}$$

$$\sum_{j=1}^{N_{hub}} E_{j,i}^{out} = E_i^{demand}, \quad i \epsilon \{e, h, c, a\} \tag{11}$$

- Capacity limits at the inputs of all energy units that make up the system should be limited to the following inequality constraint:

$$E_{j,i}^{in,min} \leq E_{j,i}^{in} \leq E_{j,i}^{in,max}, \; i \epsilon \{e, g, h\}, j = 1, \dots, n_i \tag{12}$$

- Dispatch factors of the energy hubs which determine the energy transfer between the input and output connections of the sub-units should be between 0 and 1 considering the inequality limit as below:

$$0 \leq \nu \leq 1, \quad i \epsilon \{e, g, h\}, \; j = 1, \dots, n_i \tag{13}$$

2.3. Coyote optimization algorithm

Optimization is a process to finding the best possible solution for a problem. Optimization algorithms are used to find the best fit solution of a mathematically formulated problem which under certain constraints and conditions. The fact that optimization problems encountered in the real world have become increasingly complex that has led to the need for better optimization algorithms and increased the importance of the studies in this field [16]. Especially, most optimization problems in the engineering disciplines involve the optimization of multiple competing solutions. Since there is no single optimal solution for such problems, the best possible solution is searched for in the search field which usually consists of alternative solutions [17]. Researchers have been searching to alternative algorithms for the problems that cannot be solved or difficult to solve with classical optimization algorithms.

Nature is the most important source of inspiration for models which developed by researchers to calculate solutions for complex problems. However, optimization plays an important role in the realization of many natural processes [18]. Due to the simplicity and flexibility of evolutionary, heuristic or meta-heuristic optimization algorithms, which have been inspired by nature and these algorithms have proved successful in solving multi-purpose optimization problems. In literature, Swarm intelligence-based optimization algorithms base on the behavior of animals in nature that enact to achieving a specific purpose. Developed swarm intelligence algorithms are stochastic optimization algorithms which have base on variable and random interactions that in swarm or between swarms [19], [20].

In this paper, Coyote Optimization Algorithm (COA) that was found by J. Pierezan and L.D.S Coelho inspired by the behavior of Canis Latrans species in 2018 has presented for the solution of EHED problem. COA was developed from the adaptation of these species living in North America to environment and social conditions and it is an algorithm based on population-based swarm intelligence and evolutionary intuition. In this algorithm, unlike Gray Wolf Optimization (GWO), the social behavior and mutual experience of the coyotes that make up a coyote pack are also taken into consideration [21]–[23].

The total population of COA be determined by N_p pack number that consists N_c coyotes and the multiplication of N_p and N_c gives the number of population. The solitary or temporary coyotes are not taken into account during this process for simplification. Each coyote in the population is one of the possible solutions to the optimization problem to be solved. In addition, each coyote' s social condition in the pack is the cost of objective function. Factors such as social status, gender, temperature, snow depth, snow hardness affect the activities of a coyote in the pack. These factors are the decision variables of a global optimization problem and expressed with $\vec{x}$. Any c^{th} coyote' s social condition is *soc(set of decision variables)* at any t^{th} time is expressed as follows [21]–[23]:

$$soc_c^{p,t} = \vec{x} = (x_1, x_2, \dots, x_D) \tag{14}$$

In COA, the global coyote population is generated first. Since COA is a stochastic algorithm, the initial social conditions of the coyotes that make up the pack are determined randomly for each coyote. Creating population is done by choosing random values in the j_{th} dimension for each coyote in packs:

$$soc_{c,j}^{p,t} = lb_j + r_j \cdot (ub_j - lb_j) \tag{15}$$

In Equation 14. and Equation 15. respectively, D represents the size of the search space, lb_j is the lower limit of decision variables, ub_j is the upper limit of decision variables, and r_j is a real number that generated using the uniform probability distribution in the range [0, 1].

The objective function cost $fit_c^{p,t} \in R$ is means to be adapted to the environment of coyotes and calculated by Equation 16. :

$$fit_c^{p,t} = f(soc_c^{p,t}) \tag{16}$$

When packs are formed, coyotes are randomly assigned to the packs. However, sometimes the coyote assigned to a pack may leave the pack and can be alone or join the another pack. P_e is possibility of a coyote passing from a pack to another pack depends on coyote number within pack is defined as:

$$P_e = 0.005 \cdot N_c^2 \tag{17}$$

The fact that P_e does not have a value greater than 1 limits the number of coyotes per pack to 14. This situation leads to the diversification of interaction between the coyotes, so that the global population of packs may also have cultural changes.

The coyote packs usually have two alphas. COA accepts the one of these alphas which has better adapt to the environment as the pack leader. The leader of the p^{th} pack at any t^{th} time for minimization problems is:

$$alpha^{p,t} = \left\{soc_c^{p,t} \mid arg_{c\{1,2,....Nc\}} min f(soc_c^{p,t})\right\} \tag{18}$$

COA assumes that the coyotes are sufficiently organized to share social conditions and contribute to the protection of the pack. This is a sign of a pack intelligence and all the information from the coyotes is used to calculate the cultural trend of the pack [21]–[23]:

$$cult_j^{p,t} = \begin{cases} O_{\frac{Nc+1}{2},j}^{p,t} & , if\ Nc\ is\ odd \\ \dfrac{O_{\frac{Nc}{2},j}^{p,t} + O_{\frac{Nc+1}{2},j}^{p,t}}{2} & , otherwise \end{cases} \tag{19}$$

In Equation 19. $O^{p,t}$ is social conditions of each coyote in the p^{th} pack at any t^{th} time and can be in the range [1, D]. In addition, the coyotes' s average social conditions in pack give the cultural tendency of the pack.

Considering the birth and death events which are the beginning and end of the life cycle of all living creatures in nature, the age of coyotes in years is expressed as $age_j^{p,t} \in N$. Based on the social conditions and environmental influences of two randomly selected parents from the pack, the birth of a new coyote pup is expressed as follows [21]–[23]:

$$pup_j^{p,t} = \begin{cases} soc_{r_1,j}^{p,t} \ , & rnd_j < P_s\ or\ j = j_1 \\ soc_{r_2,j}^{p,t} \ , & rnd_j \geq P_s + P_a\ or\ j = j_2 \\ R_j \ , & otherwise \end{cases} \tag{20}$$

where r_1 and r_2 are randomly selected coyotes from the p^{th} pack, j_1 and j_2 random two dimensions of the problem, P_s is the distribution probability, P_a is the association probability, R_j a random number in the decision variable and rnd_j is a random number in the range [0, 1] which generated using a uniform probability distribution.

P_s and P_a significantly affect the cultural diversity of the coyotes that make up a pack. These two probabilities are given in Equation 21. and Equation 22. Also P_a has the same effect in both parents.

$$P_s = 1/D \tag{21}$$

$$P_a = (1 - P_s)/2 \tag{22}$$

The coyote pups born in a pack are likely to die 10%. In the COA, correlation between pack population and birth and death is provided by Algorithm 1.:

Algorithm 1. Birth and death in a pack [21]–[23]

Calculate ω and φ
if $\varphi = 1$ **then**
The pup survives and the only coyote in ω dies.
elseif $\varphi >$ **then**
The pup survives and the oldest coyote in ω dies.
else
The pup dies.
end if

where ω and φ represent, respectively the pack is that are poorly adapted to the environment than pup and the number of coyotes in this pack. In addition, another point in this algorithm is to look at the adaptation of the coyotes to the environment when deciding which coyotes of the same age will die and poorly adapted coyote dies [21]–[23].

The alpha effect (δ_1) and the pack effect (δ_2) is an assumption used by COA to demonstrate the cultural interactions of coyotes within the pack. δ_1 means a cultural difference from a random coyote to alpha in the pack and δ_2 means a cultural difference from a random coyote found in the pack to the cultural tendency of the pack. These effects are calculated as follows by using selected coyotes with uniform probability distribution:

$$\delta_1 = alpha^{p,t} - soc_{cr1}^{p,t} \tag{23}$$

$$\delta_2 = cult^{p,t} - soc_{cr2}^{p,t} \tag{24}$$

Updating the new social situation of a coyote is done using δ_1 and δ_2 as follows:

$$new\_soc_c^{p,t} = soc_c^{p,t} + r_1 \cdot \delta_1 + r_2 \cdot \delta_2 \tag{25}$$

In Equation 25., r_1 and r_2 are weights of alpha and pack effect. These values are initially determined by a uniform probability distribution in the range [0, 1]. Then, the new social situation of coyote is evaluated by using Equality 26. and Equality 27. and it is decided whether the new social situation is better than the old one:

$$new\_fit_c^{p,t} = f(new\_soc_c^{p,t}) \tag{26}$$

$$soc_c^{p,t+1} = \begin{cases} new\_soc_c^{p,t}, new\_fit_c^{p,t} < fit_c^{p,t} \\ \quad soc_c^{p,t} \quad , otherwise \end{cases} \tag{27}$$

Thus, the global solution of optimization problem is determined as the social condition of the coyote that best adapts itself to the environment. The pseudo code of COA is given in Algorithm 2. In this paper, N_p and N_c respectively, have selected as 5 and 14 to solve the EHEDP.

Algorithm 2. Pseudo code of the COA [21]–[23]

```
Initialize global population by using Np and Nc each (Eq. 15).
Verify the coyote adaptation (Eq. 16).
while stopping criterion is not achieved, do
for each p pack do
    Define the alpha in pack (Eq. 18).
    Calculate pack' s social tendency (Eq. 19).
    for each wolf in p pack do
        Update social conditions (Eq. 25).
        Compute new social conditions (Eq. 26).
        Evaluate new social situations for adaptation (Eq. 27).
    end for
    Birth and death events (Eq. 20 and Eq. 1).
end for
Coyote crossing between packs (Eq. 17).
Update the ages
end while
Choose the coyote that best adapts to the environment as a global solution.
```

3. Results

In this study, the performance of the COA proposed for the EHED problem has tested with an energy hub model that including 7 hubs and 17 control variables. The energy inputs of model are provided from 13 different sources which are 4 electricity source, 7 natural gas source and 2 heat energy source. The energy demands of EH model has chosen as respectively, *1.6 pu* electricity, *1.2 pu* heat, *0.2 pu* cooling and *1.5 pu* compressed air. In addition, 17 control variables include energy sources and dispatch factors. The test system data is given in Appendix A. and Appendix B. The proposed Algorithm has tested for EH model by using MATLAB software on a 64-bit operating system PC which has AMD Ryzen ™ 7 2700X 3.7 GHz processor, 16 GB RAM. The results obtained by 30 independent runs have compared with the results of GA, PSO, MSA and SOS and the ability of COA has shown to solve the EHEDP. In the results, per-unit system (pu) and monetary unit (mu) have used as units.

In this study, the COA has used only for the solution of the EH fuel cost function minimization problem in given Equation 9. as a single objective optimization problem and total losses of EH has been neglected. Table 1. shows the minimum (Min), maximum (Max), mean and standard deviation (Std) values of the fuel costs that obtained by independent running the compared algorithms 30 times. As can be seen from Table 1., better results have obtained from solutions that made with COA than compared other algorithms in Min, Max and Mean values. Also it is seen that the Std value that shows the dispersion of the solutions around the obtained Mean values found has a better result than the SOS which obtained the best results after the COA in the fuel cost.

Table 2. shows the solutions made with GA, PSO, MSA, SOS and COA for EH test system whose energy cost is to be minimized. The electricity, gas and heat energies to be consumed so that the EH that make up the test system can meet the demands such as electricity, heating and cooling are calculated separately with compared five algorithms. The total fuel costs (CF) obtained with the cost function from Equation 9. that based on the consumed energies which calculated by the algorithms are also shown in the table. When the energy costs calculated by COA in the comparison results given in Table 2. are examined, it is seen that COA has reached the best result for minimizing the energy cost of system with *2334.8313 mu*. Other algorithms results are respectively *SOS = 2330.4058 mu*, *PSO = 2355.2932 mu*, *GA = 2388.0599 mu* and *MSA = 2390.0824 mu*. Also total energy losses in hubs have calculated respectively as *SOS = 0.5653, COA = 0.5720, GA = 1.1546, MSA = 1.2107* and *PSO = 1.2275*. In this study, although it is not aimed to minimize the total energy losses besides the energy cost, the 0.5720 value of total losses obtained by the COA is seen to be close to the nearest competitor SOS.

Table 1. Min, Max, Mean and Std values of the compared algorithms

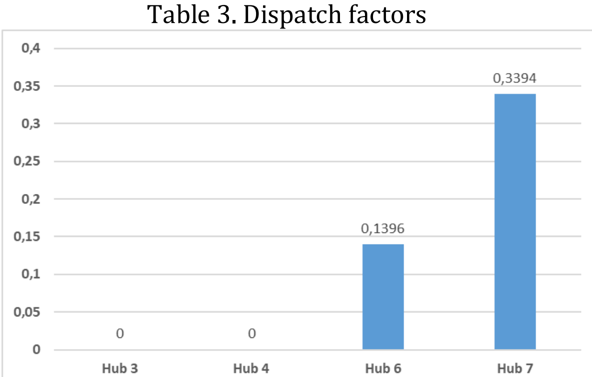
	GA	PSO	MSA	SOS	COA
Min	2388.0599	2355.2932	2390.0824	2336.2166	2334.8313
Max	2418.1515	2401.5981	2400.8814	2386.4112	2364.1546
Mean	2394.8630	2363.8034	2393.8090	2347.2564	2339.5667
Std	6.6516	8.7582	4.6572	10.0690	6.7960

Table 2. Comparative results

Hub No	Energy Type	GA	PSO	MSA	SOS	COA
1	Gas	0.7897	0.6388	0.8197	0.5400	0.5000
2	Electricity	0.2146	0.2000	0.2107	0.2000	0.2000
	Gas	0.4125	0.1542	0.5568	0.1051	0.1037
3	Gas	0.8141	0.9484	0.3710	0.1507	0.1842
4	Gas	0.3448	0.3448	0.3448	0.3448	0.3458
5	Electricity	0.2001	0.2000	0.2117	0.2000	0.2000
	Gas	0.2057	0.2000	0.2547	0.2001	0.2000
	Heat	0.1330	0.1000	0.1001	0.6999	0.6967
6	Electricity	0.1405	0.1000	0.1034	0.1000	0.1019
	Gas	0.7896	1.2157	1.1357	0.2331	0.3008
7	Electricity	0.2068	0.2001	0.2006	0.8411	0.8409
	Gas	0.2033	0.2000	0.2012	0.2007	0.2000
	Heat	0.1000	0.1256	0.1000	0.1496	0.1012
Total Production (pu)	Electricity	0.7620	0.7001	0.7264	1.3411	1.3428
	Gas	3.5597	3.7019	3.6839	1.7745	1.8345
	Heat	0.2330	0.2256	0.2001	0.8495	0.7979
CF (mu)		2388.0599	2355.2932	2390.0824	2336.2166	**2334. 8313**
Total losses (pu)		1.1546	1.2275	1.2107	0.5653	0.5720

In addition, the dispatch factors required for of Hub #3, Hub #4, Hub #6 and Hub #7 which have found with the COA for minimization of fuel cost, are given in Table 3. The dispatch factors determine how to distribute the energies at hub inputs in which it is used in the infrastructure devices that make up the energy hubs. Therefore, these factors also need to be optimized.

Table 3. Dispatch factors



For the Hub #3, dispatch factor has found to 0 with COA. Thus, in order to reduce the total fuel cost of the system, the gas input of the CHP device located in the Hub #3 has interrupted. Therefore, the heat and electrical energy obtained at the output of CHP have not contributed to meeting the total energy demand of the system. Similarly, the dispatch factor used in the Hub #4 are found to 0 with COA. This means that the compressor located in Hub #4 does not contribute to the total compressed air demand of the system. The dispatch factors calculated with COA for Hub #6 and Hub #7 determine the ratio at which the electricity generated by CHPs in hubs will be distributed in other infrastructure devices.

4. Conclusion

In this study, a new algorithm COA which based on swarm intelligence and metaheuristic has been proposed for the solution of EHED problem. Minimization of the fuel cost been achieved in EHED which is a non-linear, non-convex, non-smooth, non-differential, and high-dimensional optimization problem. The results obtained by using COA has compared with GA, PSO, MSA and SOS. The results showed that the proposed algorithm can be used for multi-objective, highly non-linear, non-convex, non-smooth, non-differential, and high-dimensional optimization problems. Moreover, easy implementation and accuracy of the algorithm has been demonstrated by fulfilling all the system constraints. Thus, the COA showed to provide better results than compered other algorithms for EHED problem.

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Appendices

Appendix A. Hub data [3], [4]

Hub No	Efficiency
1	$\eta_{CHP_e} = 0.3, \eta_{CHP_h} = 0.4$
2	$\eta_T = 1 , \eta_{CHP_e} = 0.27, \eta_{CHP_h} = 0.41$
3	$\eta_{CHP_e} = 0.31, \eta_{CHP_h} = 0.38, \eta_{GF} = 0.8$
4	$\eta_{CHCP_e} = 0.3, \eta_{CHCP_h} = 0.31, \eta_{CHCP_c} = 0.29, \eta_{c_a} = 0.7, \eta_{c_h} = 0.2$
5	$\eta_T = 0.97, \eta_{CHP_e} = 0.32, \eta_{CHP_h} = 0.44, \eta_{HE} = 1$
6	$\eta_T = 0.99, \eta_{CHP_e} = 0.3, \eta_{CHP_h} = 0.32, \eta_{c_a} = 0.59, \eta_{c_h} = 0.21$
7	$\eta_T = 1, \eta_{CHP_e} = 0.32, \eta_{CHP_h} = 0.41, \eta_{c_a} = 0.6, \eta_{c_h} = 0.2$

Appendix B. Energy sources data [3], [4]

Entire Energy	Cost coefficients of entire energy					Energy production limits (pu)	
	a (mu)	b (mu/pu)	c (mu/pu²)	d (rad/pu)	e (mu)	E_{min}	E_{max}
Gas	20	150	65	-	-	0.5	3.4
Electricity	30	180	60	140	4	0.2	1.25
Gas	20	170	90	-	-	0.1	1
Gas	25	120	50	-	-	0.15	1
Gas	10	220	60	-	-	0.1	3.2
Electricity	10	220	160	190	3.6	0.2	1.1
Gas	20	200	100	-	-	0.2	1.8
Heat	12	170	210	-	-	0.1	0.7
Electricity	80	200	25	100	4.2	0.1	0.75
Gas	25	100	40	-	-	0.2	1.9
Electricity	95	130	300	90	4.9	0.2	1.9
Gas	29	220	330	-	-	0.2	1
Heat	32	135	110	-	-	0.1	0.5