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Grey Wolf Optimization Algorithm-Based Hybrid Energy Storage System Controller Design for Electric Vehicles

Aydın BOYAR[1] Yasin KABALCI[2*] Ersan KABALCI[1]

[1] Nevsehir Haci Bektas Veli University, Faculty of Eng. and Arch, Department of Electrical and Electronics Engineering, Nevsehir, Türkiye

[2] Niğde Ömer Halisdemir University, Faculty of Engineering, Department of Electrical and Electronics Engineering, Nigde, Türkiye

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Anahtar Kelimeler

Elektrikli araçlar
Hibrit enerji depolama sistemleri
Metasezgisel algoritma
Gri kurt optimizasyonu

Graphical/Tabular Abstract (Grafik Özet)

In this study, grey wolf optimization algorithm based hybrid energy storage system controller design for electric vehicles was carried out. / Bu çalışmada, elektrikli araçlar için gri kurt optimizasyon algoritması tabanlı hibrit enerji depolama sistemi kontrolcü tasarımı gerçekleştirilmiştir.

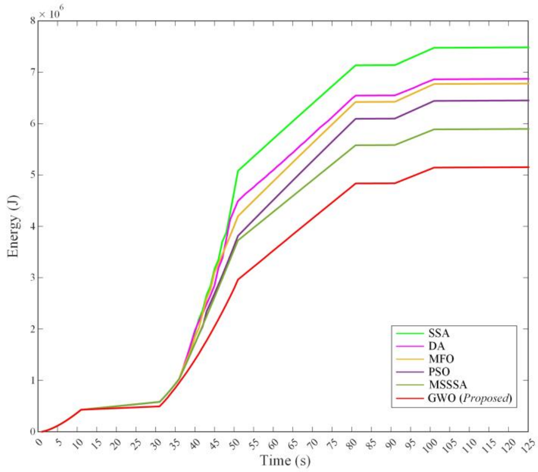

***Figure A**: The change in energy consumption for electric vehicles over time /**Şekil A:** Elektrikli araçlar için enerji tüketiminin zaman içindeki değişimi*

Highlights (Önemli noktalar)

- *Grey wolf optimization algorithm based hybrid energy storage system controller for electric vehicles is developed. / Elektrikli araçlar için gri kurt optimizasyon algoritması tabanlı hibrit enerji depolama sistemi denetleyicisi geliştirilmiştir.*
- *The proposed design provided much better performance than the methods in the literature. / Önerilen tasarım literatürdeki yöntemlere göre çok daha iyi performans sağlamıştır.*
- *The proposed system is much superior to previous methods and reduces energy consumption by 12.88%. / Önerilen sistemin literatürdeki önceki yöntemlere göre çok daha üstün olduğu ve enerji tüketimini %12,88 oranında azalttığı tespit edilmiştir.*

Aim (Amaç): *The aim of this study is to design a high-performance grey wolf optimization algorithm-based hybrid energy storage system controller for electric vehicles. / Bu çalışmanın amacı elektrikli araçlar için yüksek performansa sahip gri kurt optimizasyon algoritması tabanlı hibrit enerji depolama sistemi kontrolcü tasarımı gerçekleştirmektir.*

Originality (Özgünlük): *According to the methods in the literature, the high-performance grey wolf optimization algorithm-based hybrid energy storage system controller has been designed for electric vehicles. / Literatürde yer alan yöntemlere göre yüksek performanslı gri kurt optimizasyon algoritması tabanlı hibrit enerji depolama sistemi kontrolcüsü elektrikli araçlar için tasarlanmıştır.*

Results (Bulgular): *It has been observed that the proposed system is much superior to its strongest competitor, the master-slave salp swarm optimization algorithm-based controller, and reduces energy consumption by 12.88%. / Önerilen sistemin en güçlü rakibi olan efendi-köle salp sürüsü optimizasyon algoritması tabanlı kontrolcüye göre çok daha üstün olduğu ve enerji tüketimini %12,88 oranında azalttığı gözlemlenmiştir.*

Conclusion (Sonuç): *The developed system in this study achieved less energy consumption under the same conditions compared to existing systems in the literature. / Bu çalışmada geliştirilen sistem literatürdeki mevcut sistemlere göre aynı koşullar altında daha az enerji tüketimi elde etmiştir.*

*Corresponding author, e-mail: yasinkabalci@ohu.edu.tr DOI: 10.29109/gujsc.1475819

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Abstract

Electric vehicles (EVs) present several benefits over conventional internal combustion engine vehicles. They emit zero tailpipe emissions, thereby aiding in the reduction of air pollution and the mitigation of climate change. In addition, EVs tend to have lower operating expenses due to cheaper electricity compared to gasoline or diesel. They also provide a smoother and quieter driving experience. Furthermore, EVs help promote energy independence by decreasing dependence on fossil fuels. Overall, they represent a cleaner, more sustainable transportation option for the future. However, EVs encounter some important constraints such as inefficiency of energy consumption management, charging time, and battery range problems. To address these challenges, hybrid energy storage systems (HESSs) offer a solution by combining different energy storage technologies. These systems can improve energy efficiency, reduce charging times, and extend the driving range of EVs, making them more practical and appealing to consumers. In this study, a new controller design is realized using the grey wolf optimization (GWO) algorithm, and the energy consumption demands of EV HESS are optimized with the designed system. The performance results of the proposed system are compared with other energy management systems in the literature, and it is concluded from this study that the proposed system is much superior to previous methods and typically reduces energy consumption by 12.88%.

Elektrikli Araçlar için Gri Kurt Optimizasyon Algoritması Tabanlı Hibrit Enerji Depolama Sistemi Kontrolcü Tasarımı

Makale Bilgisi

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Öz

Elektrikli araçlar (EA'lar), geleneksel içten yanmalı motorlu araçlara göre çeşitli avantajlar sunmaktadır. Sıfır egzoz emisyonu yayıyorlar, böylece hava kirliliğinin azaltılmasına ve iklim değişikliğinin hafifletilmesine yardımcı olmaktadırlar. Ayrıca EA'lar, elektriğin benzin veya dizele kıyasla daha ucuz olmasından dolayı daha düşük işletme giderlerine sahip olma eğilimindedir. Aynı zamanda daha yumuşak ve sessiz bir sürüş deneyimi sağlarlar. EA'lar fosil yakıtlara olan bağımlılığı azaltarak enerji bağımsızlığının desteklenmesine yardımcı olmaktadırlar. Genel olarak gelecek için daha temiz, daha sürdürülebilir bir ulaşım seçeneğini sunmaktadırlar. Ancak EA'lar, enerji tüketimi yönetiminin verimsizliği, şarj süresi ve batarya menzili sorunları gibi bazı önemli kısıtlamalarla karşılaşmaktadır. Hibrit enerji depolama sistemleri (HEDS'ler), bu zorlukların üstesinden gelmek için farklı enerji depolama teknolojilerini birleştirerek bir çözüm sunmaktadır. Bu sistemler enerji verimliliğini artırabilir, şarj sürelerini azaltabilir ve EA'ların sürüş menzilini genişleterek onları daha pratik ve tüketiciler için daha çekici hale getirebilir. Bu çalışmada, gri kurt optimizasyon (GKO) algoritması kullanılarak yeni bir kontrolör tasarımı gerçekleştirilmiş ve tasarlanan sistem ile EA HEDS'in enerji tüketim talepleri optimize edilmiştir. Önerilen sistemin performans sonuçları literatürdeki diğer enerji yönetim sistemleriyle karşılaştırılmış olup bu çalışmada önerilen sistemin önceki yöntemlere göre çok daha üstün olduğu ve enerji tüketimini tipik olarak %12,88 oranında azalttığı sonucuna varılmıştır.

1. INTRODUCTION (GİRİŞ)

Electric vehicles (EVs) are transforming the automotive sector by providing a viable and environmentally friendly option to conventional gasoline-powered vehicles. Unlike conventional cars that rely on internal combustion engines fueled by gasoline, EVs utilize electricity stored in

*Corresponding author, e-mail: yasinkabalci@ohu.edu.tr
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rechargeable batteries onboard for power [1], [2], [3]. This fundamental difference brings several key benefits. The first of them is that EVs emit zero tailpipe emissions, thereby diminishing air pollution and greenhouse gas emissions, which are significant contributors to climate change. By transitioning to EVs, carbon footprint can be significantly decreased, and improved air quality in urban areas. Secondly, electric motors possess inherent efficiency advantages over internal combustion engines, effectively converting a greater portion of energy from the battery into forward motion. This means EVs require less energy to travel the same distance, resulting in lower operating costs and reduced reliance on finite fossil fuels. Thirdly, possess fewer moving components compared to traditional vehicles, thereby leading to reduced maintenance expenses over the vehicle's lifetime. Additionally, electricity is typically cheaper than gasoline, leading to lower fueling costs for EV owners. Another one is that electric motors operate quietly and provide smooth acceleration, offering a more pleasant driving experience compared to noisy and vibration-prone gasoline engines. Lastly, the rapid advancement of EV technology has led to improvements in battery range, charging infrastructure, and vehicle performance. Modern EVs can travel hundreds of miles on a single charge and charge quickly at home or public charging stations [3], [4].

The development of battery technology has led to improved battery performance. However, excessive and continuous charging or discharging of batteries can shorten their lifespan and diminish the efficiency of the system [5]. On the other hand, supercapacitors (SCs) are able to offer the advantage of high instantaneous power. Therefore, integrating a SC with a battery in a Hybrid Energy Storage System (HESS) can enhance the battery's lifespan and the overall effectiveness of the vehicle [6]. Moreover, the presence of SCs extends the range of an EV by providing fast power while accelerating and enabling the battery to recover energy when braking [7]. Moreover, the evolution of battery technology has notably enhanced the performance and driving range of EVs, addressing a key concern for potential customers. The significance of EVs transcends personal transportation, as the transportation industry significantly contributes to the emission of greenhouse gases. Wide-scale adoption of EVs can play a pivotal role in reducing carbon dioxide emissions and combatting climate change. Additionally, EVs have the capacity to provide decentralized energy storage and integrate with the grid, thereby enabling the seamless integration of renewable energy sources and encouraging sustainability [6].

Recent research has focused on improving HESS in plug-in hybrid EVs (PHEVs) to reduce battery aging expenses and enhance fuel economy. A novel PHEV power system configuration has been developed integrating a battery pack including an internal combustion engine (ICE), and SC [8]. This configuration enhances the fuel efficiency of the PHEV by associating the battery and SC with the DC-bus line and powering the driving (electric) motor. Experimental results indicate that HESS systems can remarkably prolong battery life and reduce operating costs [9]. The SC increases vehicle acceleration and provides complementary power, thereby improving acceleration performance while extending battery and SC lifespan. Employing HESS technology shows significant potential in enhancing both the economic efficiency and the performance of PHEVs. However, a notable challenge arises: effectively distributing power requirements among various components in real time. This is commonly known as the Energy Management (EM) problem [10], [11], [12].

Considerable research efforts have been devoted to devising efficient EM systems for HESSs integrating batteries and SCs in EVs. Rule-based approaches have been introduced in references [13], [14], [15], employing *if-else* paradigms derived from heuristic human experience. In those related studies, a threshold is established on the current requested by the EV motor. When the current demand surpasses this threshold, the SC is engaged to provide the necessary power, while the EV battery remains operational below the threshold. Alternative rule-based algorithms for managing HESS, discussed in references [16], [17], establish the threshold according to the power provided to the drive motor rather than its present demand. This approach takes into account the motor's requirements for both voltage and current.

Within the rule-based algorithms, predetermined current and/or power thresholds are established based on expected power demands for predefined driving cycles. However, this limitation is tackled in Reference [18] through the proposal of an adaptive power split strategy. This strategy dynamically follows the load profile of the motor in real time to assess variations in power demand and accordingly allocate power between the capacitor and the battery. Another split method is exploited in Reference [19] thanks to fuzzy logic controllers to specify the frequency of load variation. In addition, Reference [20] introduces a fuzzy rule-based HESS

EMS, featuring optimized membership functions for precise specification of thresholds. Furthermore, Reference [21] implements real-time current sensing to regulate the maximum current delivered from the battery to the drive motor, thus mitigating the risk of extreme battery discharge.

References [22], [23] propose an offline method for detecting globally optimal EMSs utilizing dynamic programming (DP). However, these approaches necessitate preliminary knowledge of the driving cycle and significant calculation capacity of the EMS controller. Reference [24] introduces an optimization problem aimed at determining the ideal sizing of both the battery and SC banks necessary for executing a rule-based algorithm for managing energy within a semi-active HESS. This optimization aims to simultaneously minimize the cost of the HESS while maximizing the driving range of the EV. Reference [25] similarly offers an optimal model for sizing the battery and SC within a semi-active HESS. However, rather than relying on predefined EMS rules, this model utilizes the power demands of diverse driving cycles to establish the constraints of the model.

Various optimization methods can be combined with rule-based algorithms to facilitate effective power allocation within HESSs. References [26], [27] constrain the search space for power allocation using a predefined set of rules. Within this framework, real-time determination of the optimal operating point is achieved through the application of metaheuristic optimization techniques. In other optimization-based studies, a new HESS for EVs is proposed in [28]. The setup employs an energy pump to sustain voltage of SCs above that of the battery during traditional driving scenarios. To address the issue of large voltage fluctuations from SC power transmission, a modulator replaces the DC/DC converter. This system enables control and optimization of energy while preserving the achievement of the driving motor [29]. The researchers in [30] focus on managing the power of energy storage systems for EVs using metaheuristic algorithms such as simulated annealing (SA) and particle swarm optimization (PSO). In a recent study, in [31], the authors investigate the performance of the master-slave salp swarm optimization algorithm (MSSSA) and compare the results of their proposed method with other popular metaheuristic algorithms such as salp swarm algorithm (SSA), dynamic algorithm (DA), moth flame optimization (MFO), and PSO.

To the best of the authors' knowledge, this is the first study that investigates the performance of the Grey Wolf Optimizer (GWO) algorithm in managing energy demand in EV HESSs. Firstly, an EV HESS system design based on GWO was conducted, followed by a comprehensive analysis of the performance of the developed management system. During the simulation studies, parameters used in previously reported systems in the literature were adopted to ensure a reliable comparison. The performance results of the proposed system were compared with rival EV HESS management systems in the literature, and it was observed that the GWO-based system proposed in this study outperforms previous methods by a significant margin.

2. SYSTEM MODEL (SİSTEM MODELİ)

An exemplary EV HESS system model is depicted in Figure 1. This model essentially contains a battery a SC module connected in parallel. Lithium-ion batteries are commonly preferred in EVs today due to their high storage capacity. However, over time, lithium-ion batteries degrade and begin to exhibit rapid discharge or charge within shorter periods. Drawing significant current may cause overheating and necessitating the regulation of current. Otherwise, while SCs possess restricted capacity, they offer the superiority of rapid charging and discharging (typically over 1 million cycles) without degradation. The use of HESS in EVs aims to provide sufficient power during the driving cycle while reducing battery degradation as much as possible. Within this framework, an appropriate control system can be designed thanks to GWO algorithm.

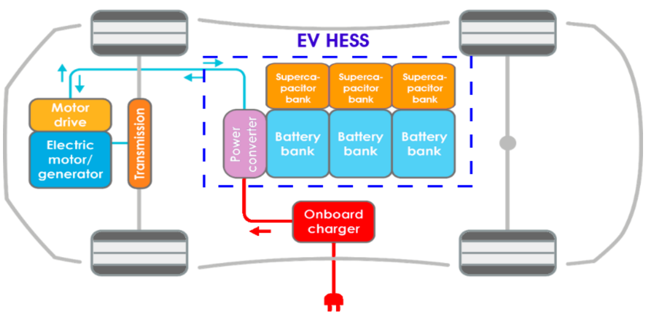


Figure 1. Block diagram of a typical EV HESS model (Tipik bir EA HEDS modelinin blok diyagramı)

Typically, a battery module with a voltage range of 200 V to 500 V and a high-capacity module ranging from 20 kWh to 100 kWh are achieved through the use of a series and parallel arrangement of cells for EVs. A suitable model characterizes the battery in terms of a voltage source and a resistor connected in series. The output voltage is based on the state of charge (SoC). The SoC parameter of any battery is mathematically defined by the following equation.

$$SoC_B = \frac{Q_B}{Q_n} = \frac{Q_B}{Q_{init}} \times SoC_{B_{init}} \tag{1}$$

where Q_B represents the stored energy while Q_n stands for the nominal capacity within the battery module. The battery voltage, V_B, within the range of 15% to 90%, is approximately represented by:

$$V_B = V_B - \left(\zeta \times \Delta SoC_B\right) \tag{2}$$

where ζ is a correction parameter with a value of 0.0007. Additionally, the current drawn from the battery, I_B, is given as,

$$I_B = \frac{V_B \pm \sqrt{{V_B}^2 - 4R_B - P_B}}{2R_B} \tag{3}$$

where R_B and P_B represent internal resistance of battery and the total power of battery, respectively.

The SCs have much higher capacity when compared to typical capacitors operating at low voltage values. The SCs used in EV HESSs typically have a capacitance of approximately 400 F. These capacitors offer a significant advantage in terms of energy storage density than that of electrolytic capacitors providing high charging and discharging capabilities. Due to their very long lifespan, the life loss of SCs used to store load in EVs is negligible. The voltage at the terminals of the SCs varies linearly according to the SoC, and it can be determined based on the energy and capacitance stored in the SCs as,

$$V_{SC} = \frac{0.5 \times Q_{SC}}{C_{SC}} + \sqrt{\left(\frac{0.25 \times Q_{SC}}{C_{SC}}\right)^2 - P_{SC} \times R_{SC}} \tag{4}$$

where Q_{SC} represents the energy accumulated in the SC, C_{SC} denotes the capacitance of the SC, R_{SC} indicates the internal resistance of the SC, and P_{SC} corresponds to the load of the SC.

Similar to Equation (1), the SoC parameter of the SC can be defined as follows.

$$SoC_{SC} = \frac{Q_{SC}}{Q_{SC_n}} = \frac{Q_{SC}}{Q_{SC_{init}}} \times SoC_{SC_{init}} \tag{5}$$

In EVs, the management and improvement of HESS are accomplished through a controller that performs actions such as distributing energy demand between SC and battery modules, regulating the charging and discharging rates to increase battery lifespan, and minimizing energy losses in the system. However, the energy demand must be met by battery power and SC power. Considering system losses and a time period of 1 second, the energy demand $\left(E_D\right)$ can be expressed as,

$$E_D = P_B + P_{SC} \tag{6}$$

The outputs of energy storage modules rely on the SoC of these devices and the power demand that does not exceed the limits on the current of the battery. To ensure this, energy distribution factors K_B and K_{SC} are defined as follows [32].

$$\begin{aligned} P_B &= K_B \times E_D \\ P_{SC} &= K_{SC} \times E_D \\ K_{SC} &= 1 - K_B \end{aligned} \tag{7}$$

Energy consumption in HESS arises from various components such as losses from motors, lines, converters, capacitors, and batteries. The primary losses targeted for optimization are those associated with capacitors and batteries, which are defined as follows.

$$\begin{aligned} E &= P_B + P_{SC} + E_B^k + E_{SC}^k \\ E_B^k &= I_B^2(t) \times R_B \\ E_{SC}^k &= I_{SC}^2(t) \times R_{SC} \end{aligned} \tag{8}$$

where, P_B and P_{SC} denote the power supplied by the battery and SC, respectively, while E_B^k and E_{SC}^k denote the energy loss from the battery and the energy loss from the SC, respectively.

When the SoC is high for both the battery and the SC (e.g., close to 1), the energy distribution between the battery and the SC will have little or no effect. In this case, the optimization process is constrained only by current limits, and the constraints can be expressed as the following equations:

$$
\begin{aligned}
& I_{B_{\min}} \leq I_B \leq I_{B_{\max}} \\
& I_{SC_{\min}} \leq I_{SC} \leq I_{SC_{\max}} \\
& 4R_B \times P_{SC} \leq V_B^2
\end{aligned}
\tag{9}
$$

The objective function of the optimization problem under constraints given by Equation (9) can be defined as follows:

$$E_{Total} = \min \sum \left(E_B(t) + E_{SC}(t) \right) \tag{10}$$

$$E_B(t) = I_B(t) \times \left(\left(V_B^t(t) \times \cos\theta_B(t) \right) + R_B \right) \tag{11}$$

$$E_{SC}(t) = I_{SC}(t) \times \left(\left(V_{SC}^t(t) \times \cos\theta_{SC}(t) \right) + R_{SC} \right) \tag{12}$$

The defined objective function of the EV HESS problem is optimized thanks to GWO algorithm in this study. General information about the GWO algorithm is given in the following section.

3. GREY WOLF OPTIMIZATION ALGORITHM (GRİ KURT OPTİMİZASYON ALGORİTMASI)

The GWO algorithm is a metaheuristic algorithm reported by Mirjalili *et al*. [33], taking into account the leadership hierarchy of grey wolves and their hunting methods in nature. GWO exhibits better convergence properties compared to other population-based metaheuristic algorithms such as genetic algorithms, particle swarm optimization, ant colony optimization and firefly algorithm. However, implementing of GWO algorithm is simple and effortless when compared to other population-based optimization algorithms.

According to the leadership hierarchy of grey wolves depicted in Figure 2, there is a chain with alpha (α) wolves at the top, followed by beta (β), delta (δ), and omega (ω) wolves. As evident from the chain structure, alpha wolves are the most dominant and authoritative members of the chain. Beta wolves, situated in the lower tier, are responsible for not only commanding other lower-level wolves but also for facilitating communication among alpha wolves, delta and omega wolves. Omega wolves are selected by alpha wolves and are positioned at the lowest level. These wolves comprise a significant portion of the population and are primarily tasked with balancing the internal dynamics, safeguarding and observing population of young wolf. They are the last to feed during hunting. Wolves in the third tier are those that do not belong to other tiers and are subordinate to alpha and beta wolves but dominate omega wolves [33].

In the GWO algorithm, the hunting process is represented by tracking and tracing the prey, surrounding it, and attacking behaviors. In this algorithm, the most optimal solution obtained for the problem is considered as alpha, while beta and delta are evaluated as the second and third best solutions, respectively. Lastly, omega wolves stand for potential solutions. The characteristic hunting behaviors of grey wolves, such as tracking the prey, determining its location, and surrounding it, are analytically expressed by Equations 13 and 14.

$$D = \left| C * X_p(t) - X(t) \right| \tag{13}$$

$$X(t+1) = X_p(t) - A * D \tag{14}$$

where t represents the iteration number, A and C are coefficients, $X(t)$ represents the location of the grey wolf, and $X_p(t)$ represents the location of the prey. The coefficients A and C in Equations 13 and 14 are calculated as shown in Equations 15 and 16.

$$A = 2a * r_1 - a \tag{15}$$

$$C = 2r_2 \tag{16}$$

where r_1 and r_2 represent random numbers between $[0,1]$, while a represents a coefficient that linearly reduces from 2 to 0 while the iteration advances. The grey wolves (α, β, and δ) surrounding the prey then proceed to hunt it down. Figure 3 illustrates the hunting procedure of the grey wolves.

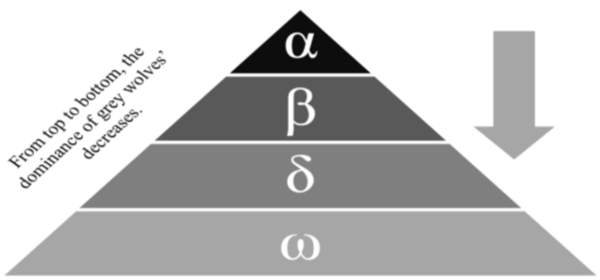


Figure 2. Grey wolf hierarchy in the GWO algorithm (GKO algoritmasındaki gri kurt hiyerarşisi)

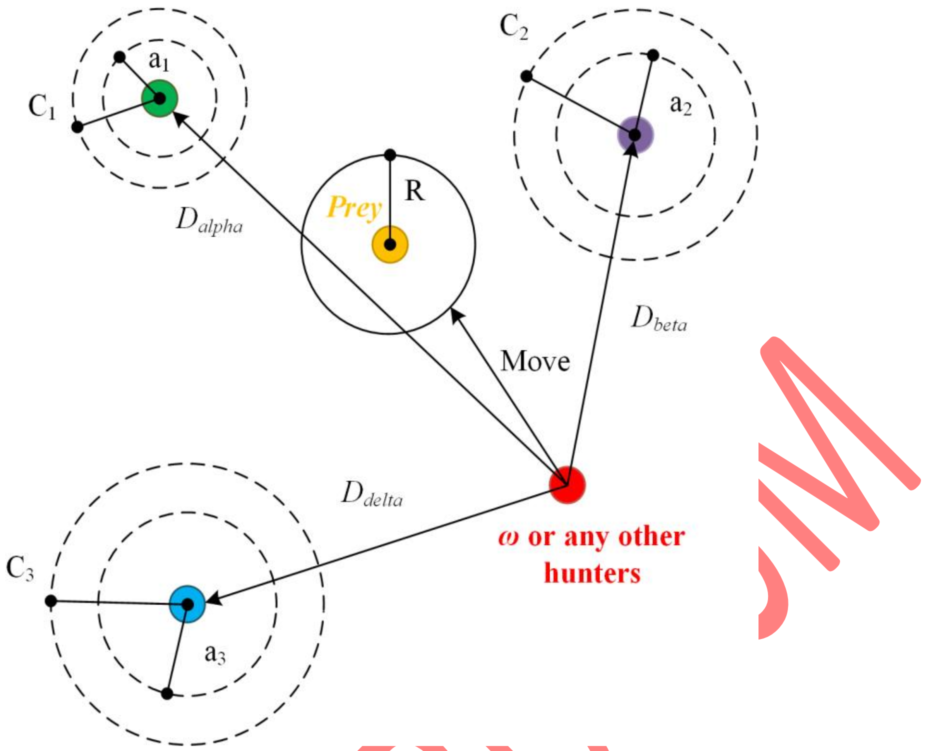


Figure 3. Hunting strategy of the grey wolves (Gri kurtların avlanma stratejisi)

The positions of the grey wolves in the hunting mechanism depicted in Figure 4 are determined by Equations 17 and 18.

$$\begin{aligned} D_\alpha &= \left|C_1 * X_\alpha(t) - X(t)\right| \\ D_\beta &= \left|C_2 * X_\beta(t) - X(t)\right| \\ D_\delta &= \left|C_3 * X_\delta(t) - X(t)\right| \end{aligned} \tag{17}$$

$$\begin{aligned} X_1 &= X_\alpha(t) - A_1 * D_\alpha \\ X_2 &= X_\beta(t) - A_2 * D_\beta \\ X_3 &= X_\delta(t) - A_3 * D_\delta \end{aligned} \tag{18}$$

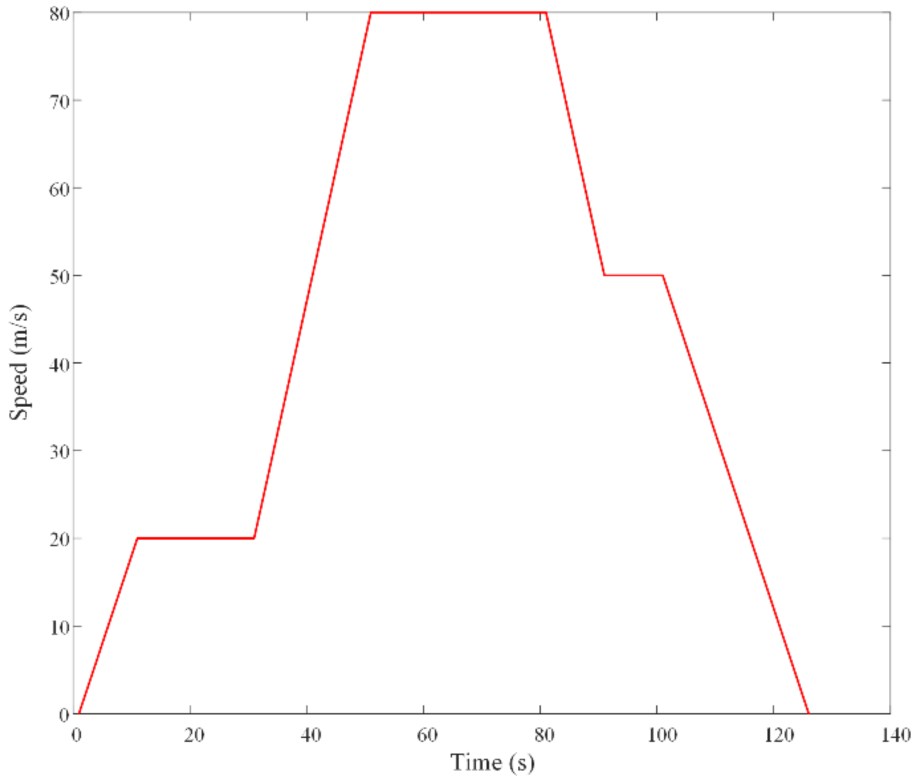
In the above equations, X_α, X_β, and X_δ show the location of the grey wolves. After the hunt, the new position of the prey is given by Equation 19.

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{19}$$

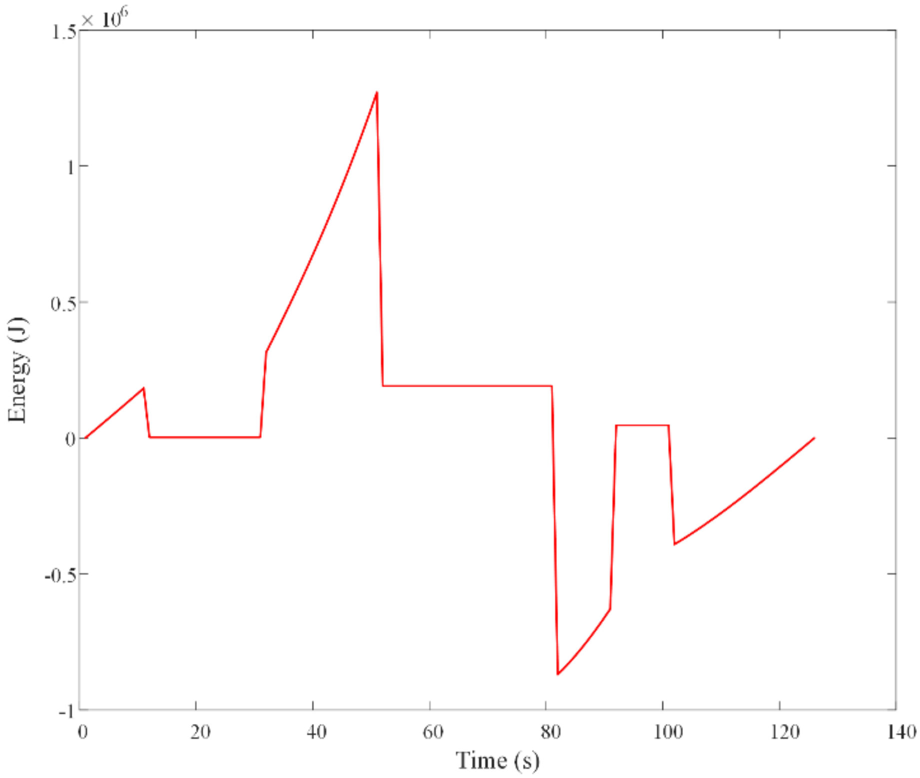
After determining the location of the prey in the GWO algorithm, the attack procedure on the prey is accomplished. The attack process occurs after the prey becomes exhausted and halts movement. Mathematically, the attack process occurs based on the value of A specified in Equation 15. The value of A diminishes according to the random variable r_1 from 2 to 0. In this situation, the variable A takes values within the range of $[-2a, 2a]$. If the value of A is bigger than 1, the grey wolves distance themselves from the prey and begin seeking a more proper target. If the value of A is less than 1, they are compelled to launch an attack on the target. The explained procedure prevents them from getting stuck in local minima. The hunting process in GWO continues till the termination criterion is satisfied or until the designated number of iterations is attained. More detailed information about the GWO algorithm can be accessed from reference [33].

4. RESULTS AND DISCUSSION (SONUÇLAR VE TARTIŞMA)

This section introduces the numerical results acquired from the comprehensive analyses conducted with the proposed EV HESS controller. During the analysis stage, the calculations involved determining the theoretical minimal energy requirements and consumption for a driving cycle. Additionally, to figure out the performance of the control strategy and enable comparison under the same conditions as the literature [31], an energy consumption curve for a duration of 125 seconds has been generated, as shown in Figure 4.



(a)



(b)

Figure 4. (a) The speed variation of the EVs over time, and (b) The variation of energy demand over time
((a) Elektrikli araçların zaman içindeki hız değişimi ve (b) Enerji talebinin zaman içindeki değişimi)

The optimization processes were performed at a rate of one per second due to the need for optimum speed in real-time optimization of the changing energy demand over time. The maximum iteration count for optimization in all algorithms was set to 100, with a search agent count of 60. Other important parameters related to EV and HESS were selected to be the same as in the literature [31], and the related parameters are listed in Table 1.

Table 1. Parameters of the experimental system (Deneysel sistemin parametreleri)

Parameter	Value
Vehicle mass	3600 kg
Friction coefficient	0,208
Air density	1,225 kg/m3
Reference area	2,34 m2
Supercapacitor capacitance	400 F
Battery voltage	350 V
Capacitor voltage	36 V
Battery internal resistance	20000 Ω
Supercapacitor internal resistance	700 Ω
Initial energy stored in battery	19800000000 J
Initial energy stored in supercapacitor	3600000 J

The numerical results obtained from the existing algorithms in the literature [31] are compared with the results obtained from the proposed GWO algorithm in this study, as shown in Table 2. All algorithms were independently run 10 times, and the minimum, average, and maximum values of the objective function results are presented in the table based on the obtained data. Additionally, the performance of all algorithms was tested on the same computer environment.

Upon examining the presented data, it can be observed that the results obtained with the HESS controller developed using the GWO algorithm in this study outperform those of other algorithms in terms of minimum, maximum, and average energy consumption values. In other words, the HESS controller designed with the GWO algorithm enables the EV to achieve the same speed profile and range with less energy consumption.

Table 2. Comparison of HESS EV energy consumption (HEDS EA enerji tüketiminin karşılaştırılması)

Algorithm	Energy Consumption Value	Computation Time
GWO - *minimum*	5.14×10^6	2.437055 s
GWO - *maximum*	5.18×10^6	3.177931 s
GWO - *average*	5.15×10^6	2.644865 s
MSSSA - *minimum*	5.90×10^6	2.989255 s
MSSSA - *maximum*	5.90×10^6	8.775863 s
MSSSA - *average*	5.90×10^6	4.516591 s
SSA - *minimum*	6.77×10^6	2.787979 s
SSA - *maximum*	7.66×10^6	3.449375 s
SSA - *average*	7.21×10^6	2.990565 s
MFO - *minimum*	6.39×10^6	2.724807 s
MFO - *maximum*	6.80×10^6	3.023435 s
MFO - *average*	6.57×10^6	2.857101 s
PSO - *minimum*	6.34×10^6	2.948035 s
PSO - *maximum*	6.53×10^6	3.353873 s
PSO - *average*	6.37×10^6	3.122244 s
DA - *minimum*	6.54×10^6	311.626785 s
DA - *maximum*	7.42×10^6	344.671427 s
DA - *average*	7.00×10^6	328.369729 s

Additionally, the computation times of metaheuristic algorithms in the design of HESS controller systems have been investigated and presented in the same table. Upon examination of the computation times, it is evident that the DA algorithm has both the lowest performance and the slowest computation capability. On the other hand, when comparing the computation times of the proposed controller's main competitor, the MSSSA-based system [31], it is observed that the GWO-based HESS controller developed in this study is faster than the MSSSA-based system.

Figure 5 illustrates the variation of battery current and supercapacitor current over time for the EV HESS system optimized with GWO algorithm. Upon examining the current curves, it is observed that the instantaneous decreases in battery current are balanced by an increase in supercapacitor current, ensuring that the energy demand is met.

The curves illustrating the variation of energy consumption over time for the EV are presented in Figure 6. Upon examination of the graph, it is clearly evident that the HESS system designed with the proposed GWO algorithm in this study achieves the least energy consumption under the same conditions. When the improvement offered by the developed system compared to its strongest competitor, i.e., the MSSSA-based controller, is calculated, it is observed that the GWO-based EV HESS control system reduces energy consumption by 12.88% under identical conditions.

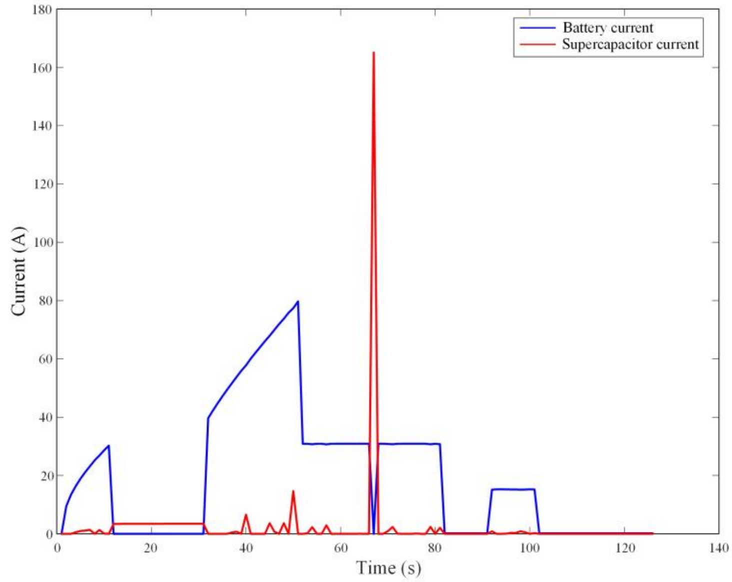


Figure 5. The distribution of current over time in an EV HESS system optimized with the GWO algorithm (GKO algoritmasıyla optimize edilmiş bir EA HEDS sisteminde akımın zaman içindeki dağılımı)

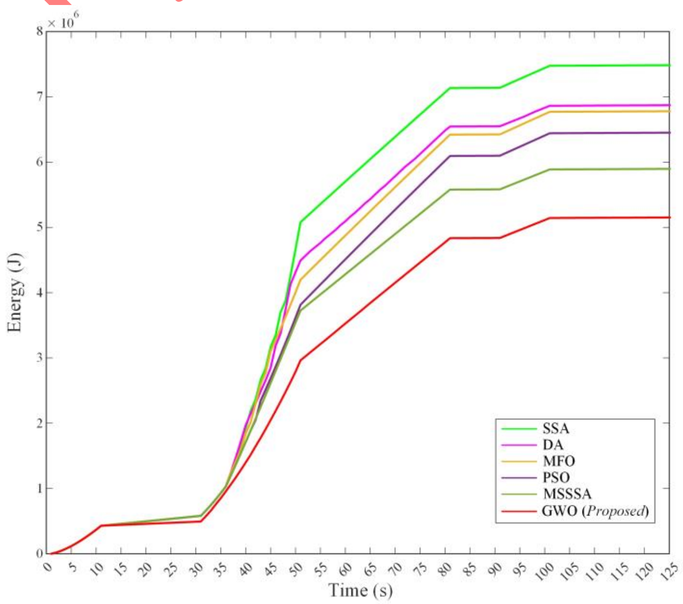


Figure 6. The distribution of current over time in the system optimized with the GWO algorithm (GKO algoritması ile optimize edilmiş sistemdeki akımın zaman içindeki dağılımı)

5. CONCLUSIONS (SONUÇLAR)

This article focuses on the use of the GWO algorithm for real-time controller design of EV HESS. The EV HESS controller designed with the GWO algorithm provided much better performance than the methods previously reported in the literature. The results obtained showed that the GWO algorithm-based EV HESS controller system proposed in this study can reach the same range using the same speed profile and with less energy consumption compared to existing systems. Moreover, according to the numerical results presented, it is calculated that the developed controller system reduces energy consumption by 12.88% compared to the MSSSA-based system, which is the best competing control algorithm.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Aydın BOYAR*:** He performed the simulation studies, analyzed the results, and carried out the writing process.

Benzetim çalışmalarını gerçekleştirdi, sonuçlarını analiz etti ve yazım işlemini gerçekleştirmiştir.

***Yasin KABALCI*:** He performed the simulation studies, analyzed the results, and carried out the writing process.

Benzetim çalışmalarını gerçekleştirdi, sonuçlarını analiz etti ve yazım işlemini gerçekleştirmiştir.

***Ersan KABALCI*:** He performed the simulation studies, analyzed the results, and carried out the writing process.

Benzetim çalışmalarını gerçekleştirdi, sonuçlarını analiz etti ve yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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