Sigma J Eng Nat Sci, Vol. 43, No. 3, pp. 933−942, June, 2025

Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2025.00081

Research Article

Innovative heating strategies for extending electric vehicle range in cold weather conditions

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ARTICLE INFO

Article history
Received: 06 March 2024
Revised: 15 April 2024
Accepted: 24 June 2024

Keywords:
Electric Vehicle; Electric Vehicle Range; Green Energy; Winter Season

ABSTRACT

This study outlines variables that may influence EV performance in real-world circumstances. Wind speed, temperature, and humidity were all taken into account during range testing. Now a day, the standard 2017 Nissan Leaf EV has lighter wheels and seats. In car racing, reducing vehicle weight is a tried-and-true performance method. According to research, modifying the form of tire rims, particularly in Tesla cars, may increase electric car range. It was projected that lowering the size of electric vehicles would extend their range. While charging the Nissan Leaf, hot air from clothes dryer was blasted below the battery for one hour to raise its temperature. This process was created to increase battery capacity so that the automobile could go farther. Hot air considerably improved the range that could be travelled after testing by recharging. This is made feasible by advancements in rechargeable battery range. The weight was removed after the third round of testing, and the distance improved somewhat. A hot air pumping system underneath electric automobiles for an extended period of time while charging in cold weather (below 0 degrees Celsius or 32 degrees Fahrenheit) investigated for potential benefits. This research focuses on the impact of a heating device on the range of electric vehicles (EVs). The study found that steel and alloy spoke rims were indistinguishable over 92.9 kilometers, and alloy wheel spokes barely held the electric car together. The research also found that at 16 degrees Celsius with dry output, the EV could drive 153 km and at 20 degrees, 171 km. However, dry heat reduced all three range estimates from 8 C's baseline of 134 km. This initiative tries to address winter range difficulties for electric vehicles.

Cite this article as: Javanjal VK, Patil LN, Mahajan KA, Patil AA, Agrawal VK. Innovative heating strategies for extending electric vehicle range in cold weather conditions. Sigma J Eng Nat Sci 2025;43(3):933−942.

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This paper was recommended for publication in revised form by Editor-in-Chief Ahmet Selim Dalkilic

INTRODUCTION

Electric Vehicles environmental, technological, and financial potential is transforming power and transportation networks [1,2]. The EV's brakes, steering, lights, and temperature control depend on the batteries. EV charging from the grid adds to the utility's workload during peak demand. Accelerating renewable energy deployment may reduce grid impacts. Renewable energy sources lessen environmental impact and boost charging system efficiency [3]. Solar electricity is becoming a cheaper grid supplement as photovoltaic (PV) module prices plummet [4]. PV systems need less fuel and work to maintain [5]. PVEV charging has improved due to advances in energy conversion technology, battery management systems, installation procedures, and design standards. EV is exposed to direct sunshine all day. It uses "charging-while-parking" to enhance electric vehicle charging choices beyond "charging by halting". Installing a solar system on the parking garage roof charging electric cars while the owner is gone is easy [6]. The authors say PV-powered charging stations have several benefits. Charging throughout the day, when load demand and power costs highest, boosts cost savings. It consumes very little fuel and generates very little CO2. Since they provide free protection from heat and rain, roof parking facilities may benefit hot-climate nations [7]. Electric vehicle charging at a PV-powered station reduces fossil fuel power plant emissions. Solar energy can charge electric automobiles even when the grid is out. PV production and V2G may minimize peak demands and stabilize microgrids. EVs differ from stationary energy storage systems due to their mobility. V2G may not occur even if enough EVs are charging at the station to reduce peak power demand or increase microgrid stability. PV-powered EV charging stations may increase microgrid resilience, although there are concerns. Figure 1 shows an electric car solar charging station's design. PV-powered EV charging stations consist of solar panels, DC/DC converters, EVs, bidirectional EV chargers, and bidirectional inverters [8]. An inverter transfers power both ways between the microgrid and the charging station. The bidirectional inverter transfers grid energy to the charging station. The microgrid and bidirectional inverter are parallel to the local load. Solar array energy may serve local consumers or supplement the power grid. MPPT is achieved in solar arrays using DC/DC converters. The bidirectional EV charger charges and discharges EVs. A bidirectional inverter and reversible EV charging are needed for microgrid electric vehicle connections [9].

Various policies support electrification across society, including the US federal government requires one million electric cars by 2015. By 2017, the Ontario Ministry of Transportation aims to create 500 electric vehicle charging stations (EVCSs) in 250 locations. The National Electric Mobility Platform (NPE) estimates that Germany will require 70,000 public on-street charging stations by 2020 [10]. China's current renewable energy use and electric vehicle energy consumption present issues that may be solved by installing a small number of solar-powered charging stations. The US, Canada, France, Germany, Japan, the Netherlands, Norway, Sweden, and the UK created the multi-government policy forum Electric Cars Initiative (EVI) in May 2017 to encourage electric vehicle adoption worldwide. South Africa, Korea, and India participate in EVI. South Africa joined the EVI in 2016 and remains. The Indian government and major automakers are promoting e-vehicles and other clean fuels to reduce vehicular pollution. Therefore, in 2013, the National Electric Mobility Master Plan (NEMMP) 2020 was established and enacted into law in 2014. Another effort is Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles (FAME). To promote electric cars, India developed the India Scheme the same year [11]. Utility users and utilities profit from this strategy. Lack of charging stations is India's top infrastructure issue. Nationwide, there are not enough charging stations. EVI members own and register 95% of global EVs [12].

Electric and plug-in hybrid electric vehicles (PHEVs) are electrified but not fully electric [13]. Figure 3 depicts the numerous charging states. PEVs can be charged 24/7 using on-board level 1 or level 2 chargers and high-power off-board chargers. A single, on-board integrated charging system for PEVs might combine the advantages of on-board and external chargers. Various organizations worldwide have specified charging levels based on car design and battery size[13]. EV charging methods include conductive charging, wireless charging, and battery swapping (Figure 4). Conductive charging is more popular and convenient. Wireless charging (WC) differs from conductivity charging by whether the power source and battery are connected. Research and development currently concentrate on WCs and battery shifting, not conductive charging [14]. EV battery chargers are crucial to the EV industry's success because public charging infrastructure drives EV adoption. It has a power factor adjustment unit, DC-DC converter, and AC-DC converter. On-board (slow charging) and off-board (fast charging) charging systems exist. The chargers may be unidirectional or bidirectional. Small one-way charging device simply transfers power from the grid to the EV. Bidirectional charging allows the vehicle's charging station to provide electricity to the battery, or "charging" a building, power grid, or private habitation while operating on public roads[15]. The availability and expansion of EV charging infrastructure may reduce the energy storage needed for onboarding, relieving EV owners. Three charging criteria are defined in SAE J1772. Home charging stations will utilize level 1 and 2 chargers, whereas public charging stations will use level 3 chargers, according to EPRI. There are many worldwide standards for electric vehicle charging stations. IEC is European-favored, although American manufacturers prefer SAE and IEEE. Japan created the CHAdeMO EV charging standard. AC and DC charging in China follow the Guobiao (GB/T) standard, and IEC AC charging standards are identical. This standard was established with ISO/IEC and the Chinese National ISO Committee. The most extensively utilized standards are IEC and SAE. IEC61852 and SAE J1772 are comparable, with a few grammatical deviations. The IEC favors "mode" over "level" to indicate output intensity.

Many academic studies have examined how to sustainably run a battery-electric vehicle (BEV). It was started with a brief summary of the research on batteries [16]. Duraisamy et al. examined how a cell-balancing management system affected battery performance. This research's main goal is not to improve electrical energy efficiency using a battery management system [17]. EV batteries are crucial, and Ramkumar et al. recommend battery management techniques to improve efficiency and performance [18]. This innovative study analyzes electric vehicle (EV) battery performance and recommends a battery management system to enhance battery life and performance. Wang et al. (2013) examined HEV line management best practices. This study uses driving behaviors rather than hybrid electric vehicles (HEVs) to calculate battery life expectancy [19]. Sun et al. (2014) predicted hybrid electric vehicle speed using a neural network-based model and an exponentially variable random Markov chain. This study offers a unique approach since it's not about battery performance [20].

The following study used technology, not machine learning. Krasopoulos et al. (2017) used multiobjective optimization to find the best speed and power curves for a tiny EV on a given route. This study is unusual since it aims to improve battery life under various driving circumstances [21]. Bozorgi et al. (2016) found that a two-option route algorithm can develop an EV speed profile. These apps employ data mining to reduce driving time or boost battery efficiency to improve EV performance [22]. Each inquiry requires a velocity map. This study stands out for its energy economics and data mining focus. Zhang et al. created a cloud-based velocity profile planner utilizing a genetic algorithm to evaluate driving profile and charge status. This scheduler for plug-in hybrid buses employs dynamic programming [23]. This study is notable since it forecasts battery life using reinforcement learning. Song et al. used machine learning to improve HEV energy efficiency. The research authors didn't use reinforcement learning to construct a BEV battery-life-considering driving profile [24].

Academics have examined reinforcement learning's automotive applications. Terapaptommakol et al. (2019) created the deep Q-network (DQN) method for autonomous vehicle control systems [25]. This technique aids trajectory planning and accident avoidance on virtual roads with actual impediments. Mohammed et al. (2020) used deep reinforcement learning to help unmanned aerial vehicles locate pollution plumes in grid regions [26]. Zheng et al. (2019) introduced a Markov decision process (MDP) to describe AGV dynamic ordering. Their method uses a deep Q-network (DQN) and mixed decision rules to find the best strategy [27]. The study focused on reinforcement learning approaches but did not address BEV battery-life-aware driving profiles. Global warming and resource depletion are two of many environmental concerns requiring human action. Cars have utilized almost 30% of oil-based energy in recent years [28]. Since oil is scarce and fuel-powered cars harm the environment, the UN and other governments have plans to restrict their production and use. These approaches aid desired growth. China aims to power 40% of its cars with renewable energy by 2030 [29]. As part of efforts to reduce carbon emissions and pollution, several companies are manufacturing eco-friendly, energy-efficient products. Example: electric cars. Electric vehicles (EVs) create less waste heat than conventional cars; therefore, they need to pump a little heat into the passenger compartment to keep it comfortable. Electric cars' driving ranges decrease while the heating system is on. The objective is to create an efficient EV heating system that saves gas money.

Research has examined many ways to warm electric automobiles. Many academic publications compare technical techniques side-by-side. Zhang et al. studied electric car range extension in 2018. The authors did not address alternate EV heating techniques that might save energy and boost range. This study compares domestic heating techniques, building on previous research [30].

PTC heating is appearing in corporate EVs. It's not energy-efficient; therefore, it uses a lot and occasionally dies. The Air Source Heat Pump (ASHP) was developed by the automobile industry to address the issue. Air-source heat pumps (ASHPs) are a great way to save energy and be comfortable[31]. The combined heating and cooling features of ASHPs save on utility expenditures. Low ambient temperatures slow the ASHP system's refrigerant flow. ASHP system efficiency would decrease. It's important to improve ASHP device performance in cold climates [32].

Adsorption air conditioning (AC) systems may help electric cars with high heating loads and short battery lives. It keeps energy consumption down in hot weather. With the fuel-burning system, heating and battery systems may be independent. This would greatly increase the vehicle's fuel economy. The thermal energy-storing heat storage system may work similarly. Remember that half of the energy in EV trash is wasted as heat. Recycling devices may save fuel and enhance heating system performance by using wasted heat. Magnetocaloric and thermoelectric technologies are also gaining prominence. These advances may soon replace heat pump (HP) systems.

MATERIALS AND METHODS

Materials

In each direction, 42 attempts with one recharge were made. The charging temperature and startup range are in Table 1. As mentioned, the link is significant. Two days had ranges under 153 km, one of which was a night the EV was driven due to an unexpected incident. Only one charging stoppage occurred during the trial while driving at night. The normal range without the dehydrator was 134 kilometers at 8 degrees Celsius (46.4 degrees Fahrenheit). The range was

Table 1. Relationship between the charging temperature and the initial range

		Temperature of Recharging	Starting Point
Temperature of Recharging	As measured by the Pearson Coefficient	1	0.475
	Significant (two-tailed)		0.012
	N	42	42
Starting Point	As measured by the Pearson Coefficient	0.478	1
	Significant (two-tailed)	0.010	
	N	42	42

Table 2. Temperature at which the battery is charged and its final operating temperature

		Mean Temp	Range End
the average temperature	As measured by the Pearson Coefficient	1	0.835
	Significant (two-tailed)		0.000
	N	42	42
Range Limit Price	As measured by the Pearson Coefficient	0.835	1
	Significant (two-tailed)	0.000	
	N	42	42

153–172 kilometers (89.5–117.5 miles) with an average of 166.86 kilometers (96.04 miles) after seven days of charging below 8 degrees Celsius. The day after testing, no range charge of 153 kilometers (87.5 miles) occurred. Heat the bottom with a dryer to increase the starting range for the next test after driving an electric car for 60 minutes. Temperature and distance are linked in the literature. As the battery warms up, storage capacity improves. Higher battery capacity immediately increases range. Table 2 shows a substantial link between temperature and the ultimate range value at 0.01. At.000, correlation coefficients are significant. A correlation value of 0.839 indicates a strong association between the variables. C-rate is the measurement of the charge and discharge current with respect to its nominal capacity.

The battery cell chemistry plays a crucial role in its performance and characteristics. Common chemistries for electric vehicle (EV) batteries include lithium-ion (Li-ion) and solid-state batteries. A typical EV battery might have a voltage of around 3.6-4.2V per cell and a capacity ranging from 20-100Ah per cell. Table 1 shows the relationship between the charging temperature and the initial range. Table 2 highlights temperature at which the battery is charged and its final operating temperature.

RESULTS AND DISCUSSION

The observations were conducted during the spring season, it may be inferred that the Indian environment exhibited higher temperatures compared to its typical conditions. The first fortnight of the year 2022 transpired inside the spring season in Canada. Based on the data shown in Table 3, it can be seen that the lowest daily average temperature recorded was 2.67°C (36.81°F), a value that is in close proximity to the freezing point of water, which is often represented as 0°C (32°F). Fort Erie had snowfall on May 8th. The mean wind velocity seen during the first fortnight of the spring season is 9.42 kilometers per hour, exhibiting a relative increase of 28.5% in comparison to the wind speeds recorded during the subsequent two weeks. Furthermore, this average wind speed is 24.6% higher when contrasted with the wind velocities observed during the fifth and sixth weeks. Table 4 throws focus on statistics for Weeks 3 and 4, Including Weather Conditions. Table 5 highlights Temperature, Relative Humidity, and Wind Speed for Weeks 5 and 6.

Table 6 displays two statistically significant deviations between the measured humidity levels and the null hypothesis. Compared to weeks 3-4 (a difference of 0.051)

Table 3. Temperature, relative humidity, and wind speed during the first two weeks

	N	Min.	Max.	Mean	Standard Deviation
the average temperature	25	2.85 C	19.85 C	9.53 C	4.85695
Wetness Index Mean	25	32.33%	91.85%	54.45%	18.856985
Average Wind Speed	25	3.80 kph	17.3 kph	9.12 kph	4.85632

Table 4. Statistics for weeks 3 and 4, ıncluding weather conditions

	N	Min.	Max.	Mean	Standard Deviation
the average temperature	25	12.33 C	24.33 C	20.42 C	4.42569
Wetness Index Mean	25	26.58%	90.25%	68.75%	20.52689
Average Wind Speed	25	4.42 kph	11.56 kph	7.53 kph	2.52362

Table 5. Temperature, relative humidity, and wind speed for weeks 5 and 6

	N	Min.	Max.	Mean	Standard Deviation
the average temperature	25	14.42 C	30.12 C	20.15 C	4.56892
Wetness Index Mean	25	46.67%	95.00%	70.25%	13.65892
Average Wind Speed	25	2.10kph	13.58 kph	7.12 kph	2.56892

and weeks 5-6 (a difference of 0.009), humidity levels were significantly lower during weeks 1 and 2. The tables 10-12 show that there is a weak correlation between humidity and the variation seen in weeks 1-2 and 5-6. During weeks 3 and 4, there was little to no meaningful relationship between humidity and variability.

The lowest temperature for weeks 1-2 was 2.67 degrees Celsius (Table 2), whereas the minimum temperatures for weeks 3-5 and 6 were 12.33 and 13.00 degrees Celsius, respectively. There were also two significant changes in humidity between the temperature data in the study and the overall sample at the.10 level. Temperatures during weeks 1-2 were.000 degrees Fahrenheit lower than those during weeks 3-4 and 5-6 combined, according to Table 7.

Wind data deviated significantly from temperature and humidity readings. As seen in Table 8, there was a

Table 6. A comparison of trial periods of two weeks by analyzing humidity in samples

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	90% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Weeks 1-3 of Humidity Weeks 3-4 of Humidity	-10.0761	25.64622	6.71052	-19.50613	-0.64607	-0.8211	20.2569	1.3079
Pair 2	Weeks 3-4 Highest Humidity (May-June)	5.9919	28.25934	7.29483	-4.44848	16.43228	2.0409	20.2569	1.6999
Pair 3	Weeks 1-2: Highest Humidity	17.3249	25.90541	6.76847	7.79466	26.85514	4.1719	20.2569	1.2659

Table 7. Samples matched by temperature test comparison of trial temperatures over a span of two weeks

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	90% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Temperature Range 1-2 -Temperature Range 3-4	-10.15456	6.40789	1.33692	-12.67992	-7.6292	-6.99156	18.87644	-0.12356
Pair 2	Temperature Range 5-6 Temperature Range 3-4	-0.05556	4.11956	0.82523	-1.69614	1.58502	-0.05156	18.87644	0.82044
Pair 3	Temperature Range 1-2 -Temperature Range 5-6	-10.22256	6.40345	1.33592	-12.7462	-7.69892	-7.04356	18.87644	-0.12356

Table 8. Evaluation of wind speed pairs comparison of two-week testing durations in relation to wind speed

		Paired Differences					t	df	Sig. (2-tailed)
		Average	Std. Deviation	Std. Error Mean	90% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Wind Weeks 1-2 -Wind 3-4	2.69	5.3202	1.2828	0.67936	4.70064	2.33	19.12	0.16
Pair 2	Wind Weeks 5-6 -Wind 3-4	0.465	4.41907	1.0813	-1.19722	2.12722	0.479	19.12	0.844
Pair 3	Wind Weeks1-2 -Wind 5-6	2.345	6.05583	1.44729	0.04994	4.64006	1.796	19.12	0.23

Table 9. Numbers describing the effective voltage range data on electric vehicle range

	N	Minimum (Kms)	Maximum (Kms)	Average (Kms)	Std. Deviation
Weeks 1-2	25	32	85	59.4	13.677
Weeks 3-4	25	35	80	57.95	15.896
Weeks 5-6	25	31	78	56.35	14.646

Table 10. Excluding data from extreme cases

Weeks 1-2			Weeks 3-4			Weeks 5-6		
N	Valid	19	N	Valid	18	N	Valid	18
Average Range (Kms)	57.28		Average Range (Kms)	57.23		Average Range (Kms)	58.29	
Median	59.23		Median	53.23		Median	57.23	
Std. Deviation	11.507		Std. Deviation	13.729		Std. Deviation	11.286	
Minimum	31.23		Minimum	39.23		Minimum	44.23	
Maximum	69.23		Maximum	76.23		Maximum	77.23	

Table 11. Correlation scores for 3 factors (temperature, humidity, wind speed) with range in weeks 1-2

		Range	Average Temperature	Average Humidity	Average Wind Speed
Range	Pearson Correlation	1	-.085	.259	-.056
	Sig. (2-tailed)		.753	.265	.658
	N	20.589	20.589	20.589	20.589
Temperature	Pearson Correlation	0.504	1.589	0.512	0.897
	Sig. (2-tailed)	1.311	0.589	1.337	0.775
	N	25	25	25	25
Humidity	Pearson Correlation	0.843	0.512	1.589	0.721
	Sig. (2-tailed)	0.869	1.337	0.589	1.167
	N	25	25	25	25
Wind Speed	Pearson Correlation	0.497	0.897	0.721	1.589
	Sig. (2-tailed)	1.288	0.775	1.167	0.589
	N	25	25	25	25

significant variation in wind speed between weeks 1-2 and 2-4. Wind speeds differed by just 0.35 kilometers per hour between weeks 3-4 and weeks 5-6.

Table 9 shows the weeks 1-2 EV range in kms. The outlier (83 Kms) was larger than all other figures in all experiments, favorably skewing the results. As noted in Table 3, weeks 1 and 2 had greater average wind speeds, and some extremely strong tail winds increased EV range.Trip results to and from Fort Erie, Ontario, are in Table 10. These findings were achieved under three testing conditions: no weight change (weeks 1-2), replacing the wheel rims (weeks 3–4), and changing both the seats and rims (weeks 5–6). Weeks 1 and 2 averaged 56.05 kilometers after removing a weather-related range number that was greater than "normal". The range increased 19% above usual on May 15 due to a strong tail wind. Weeks 3 and 4 (Table 8) were canceled due to traffic and weather. Due to severe head winds and battery consumption, the vehicle had 33 kilometers of range on May 20. May 28 brought heavy rain and traffic. When it rained, the power-operated windshield wipers were used. Weeks 3 and 4 averaged 56,000 kilometers. Due to anomalous weather and a cold recharge, weeks 5 and 6 deleted outliers 29 and 31. On May 10, 31 kilometers of electricity were consumed, and on May 15, 10.3 kilometers per hour of tail winds occurred. The automobile was charged all night on June 11 and didn't require the one-hour charge after extensive use. The average weekly mileage for weeks 5 and 6 was 57.06 kilometers. Subtracting 24.18 kg (53.2 lbs) increases the range by 1.02%. Table 10 shows the excluded data from extreme cases.

In Table 11, the Pearson correlation coefficients between temperature, humidity, and wind speed all get low marks, indicating weak ties to EV range. There is little to no difference between the three correlation coefficients .10. All studies anticipated that temperature would have an effect on EV range. Possible causes for the lack of a significant correlation include (1) too few trials, or (2) too little separation between the two groups.

The findings from weeks 3 and 4 demonstrate a similar lack of strong correlation between temperature, humidity, wind speed, and electric vehicle (EV) range, as shown in weeks 1 and 2. The statistical analysis revealed that none of the three component association coefficients exhibited statistical significance, as shown in Table 12. Range in Weeks 5-6 for Three Factors of Correlation (Temperature, Humidity, Wind Speed) are shown in Table 13.

This research focuses on the impact of a heating device on the range of electric vehicles (EVs) in Canada and the northern US. The study found that steel and alloy spoke rims were indistinguishable over 92.9 kilometers, and alloy wheel spokes barely held the electric car together. The research also found that at 16 degrees Celsius with dry output, the EV could drive 153 km and at 20 degrees, 171 km. However, dry heat reduced all three range estimates from 8 C's baseline of 134 km. The study found that a weight loss of 145.08 kg (319.2 lb) seems to cause a double-digit increase in EV range. The research suggests that lighter materials may help a smaller electric vehicle's battery. Classic gas-powered vehicles like Nissan and Ford had readily interchangeable seats and wheels, but increased EV range requires early and continued intense study. The study also found that rims with the proper mass were hard to locate, and the weight of Amazon rims was surprising. Future empirical studies should focus on customized, lightweight wheel rims.

This study explores the advancements in electric vehicle (EV) heating systems, focusing on their systems, technology, and challenges. The PTC system has been the preferred heating technique due to its low thermal resistance and efficiency, but the HP system is being replaced due to its lower fuel efficiency. New circulation techniques and refrigeration injection systems are being explored to improve performance at low temperatures and surface frost. Research

Table 12. Range in weeks 3 and 4 for three factors of correlation (temperature, humidity, wind speed)

		Range	Mean Temp	Mean Humidity	Mean Wind Speed
Range	Pearson Correlation	1	-.032	.012	-.019
	Sig. (2-tailed)		.909	.993	.939
	N	25	25	25	25
Temperature	Pearson Correlation	-0.0258	1.0012	-0.0008	-0.2718
	Sig. (2-tailed)	0.9102	0.0012	0.9952	0.2462
	N	25	25	25	25
Humidity	Pearson Correlation	0.0032	-0.0008	1.0012	-0.0888
	Sig. (2-tailed)	0.9942	0.9952	0.0012	0.7082
	N	25	25	25	25
Wind Speed	Pearson Correlation	-0.0168	-0.2718	-0.0888	1.0012
	Sig. (2-tailed)	0.9402	0.2462	0.7082	0.0012
	N	25	25	25	25

Table 13. Range in weeks 5-6 for three factors of correlation (temperature, humidity, wind speed)

		Range	Average Temperature	Average Humidity	Average Wind Speed
Range	Correlation Pearson	1	-.226	.253	-.259
	Sig. (2-tailed)		.329	.368	.395
	N	25	25	25	25
Temperature	Pearson Correlation	-0.2098	1.0012	-0.2608	0.3692
	Sig. (2-tailed)	0.3742	0.0012	0.2652	0.1122
	N	25	25	25	25
Humidity	Pearson Correlation	0.2012	-0.2608	1.0012	-0.0158
	Sig. (2-tailed)	0.3992	0.2652	0.0012	0.9442
	N	25	25	25	25
Wind Speed	Pearson Correlation	-0.1988	0.3692	-0.0158	1.0012
	Sig. (2-tailed)	0.4002	0.1122	0.9442	0.0012
	N	25	25	25	25

is also being conducted to reduce the power grid load of EV heating systems, with EV adsorption heating potentially improving battery life and range. Fuel-burning heaters may save gas, while heat storage and waste heat recovery systems can lower battery load and extend lifespan. Magnetocaloric and thermoelectric phenomena make electric vehicle heaters greener. EVs are becoming practical for long-distance North American travel, and design must be rethought to boost range. Heating options are essential for optimal battery temperature during charging in autumn, spring, and winter. As electric automobile research is new, practical applications may improve, with more testing and testing providing more reliable findings

The article also examines the impact of HVAC energy use on electric vehicles, focusing on HVAC systems, EV range forecasting and optimization, external impacts, and HVAC refrigerants. Future research on thermal comfort and range optimization may be vital for Evs.

CONCLUSION

The study on air conditioning system optimization for electric vehicles highlights the need to enhance EV performance and efficiency. Improving the air conditioning system can significantly increase EV range, crucial for sustainable transportation. The research emphasizes the feasibility and necessity of enhancing EV range for wider adoption. Energy-efficient technologies and thermal management strategies can reduce energy consumption, extend battery lifespan, and improve passenger comfort. Balancing passenger well-being and energy efficiency is vital, especially in extreme climates. This research focused on the impact of a heating device on the range of electric vehicles (EVs). The study found that steel and alloy spoke rims were indistinguishable over 92.9 kilometers, and alloy wheel spokes barely held the electric car together. The research also found that at 16 degrees Celsius with dry output, the EV could drive 153 km and at 20 degrees, 171 km. However, dry heat reduced all three range estimates from 8 C's baseline of 134 km. The study provides guidance for automotive manufacturers and policymakers to promote the sustainability and attractiveness of electric vehicles. Overall, optimizing the air conditioning system is a key step towards improving EV performance and driving widespread adoption.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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