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Effects of High Ambient Temperature on Electric Vehicle Efficiency and Range: Case Study of Kuwait

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Abstract: The use of electric vehicles (EVs) provides a pathway to sustainable transport, reducing emissions and contributing to net-zero carbon aspirations. However, consumer acceptance has been limited by travel range anxiety and a lack of knowledge about EV technology and its infrastructure. This is especially the case in hot and oil-rich areas such as Kuwait, where transport is predominantly fossil fuel-driven. Studying the effects of high ambient temperature on EV efficiency and range is essential to improve EV performance, increase the user base and promote early adoption to secure more environmental benefits. The ability to determine the energy consumption of electric vehicles (EVs) is not only vital to reduce travel range anxiety but also forms an important foundation for the spatial siting, operation and management of EV charging points in cities and towns. This research presents an analysis of data gathered from more than 3000 journeys of an EV in Kuwait representing typical vehicle usage. The average energy intensity and consumption of the car/kilometre travelled were calculated for each journey, along with ambient temperature measured by the vehicle. The analysis indicates that energy intensity reaches a minimum at a starting temperature between 22 °C and 23 °C. Energy intensity rises with decreasing temperature below this point and with increasing temperature above this point. The results show that many vehicle journeys started with high temperatures, with about half of journeys starting at 30 °C or above and approximately a quarter at 40 °C or above. Fitting a model to the empirical data for trip starting temperature and energy intensity, average efficiency is impacted at high car temperatures, with energy intensity modelled at 30 °C and 40 °C to be higher by 6% and 22%, respectively. These findings have implications for vehicle range, EV charging infrastructure and car storage and parking provision.

Keywords: EV electric consumption; ambient temperature; EV auxiliary loads; energy efficiency; social interaction effects

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Citation: Hamwi, H.; Rushby, T.; Mahdy, M.; Bahaj, A.S. Effects of High Ambient Temperature on Electric Vehicle Efficiency and Range: Case Study of Kuwait. *Energies* **2022**, *15*, 3178. https://doi.org/10.3390/en15093178

Academic Editor: Javier Contreras

Received: 29 March 2022
Accepted: 18 April 2022
Published: 27 April 2022

1. Introduction

The Kuwaiti government plans to produce 15% of its total domestic energy demand from renewable energy sources by the year 2030 [1]. This ambitious strategy is a response to fears over the surge in the national energy supply from hydrocarbon sources in Kuwait since 1990. By the end of 2019, Kuwait installed fossil power plants with a combined capacity of 19.3 GW, of which renewable energy accounts for only 106 MW, or less than 1% of total capacity [2]. At the same time, Kuwait is experiencing an exponential growth in internal combustion engine vehicles as a result of the low prices of these types of vehicles and the low cost of fuel [3]. The transport infrastructure is under stress due to high demand, where car ownership exceeds 3.3 per capita [4]. A recent study emphasised that one of the main causes of high pollution levels in Kuwait is vehicle traffic congestion, visualised by an ever-increasing number of cars queuing on major highways such as the King Abdulaziz (Fahaheel) and the 5th and 6th Ring Roads [3,4]. Previous studies have recommended the development of new strategies that aim to reduce and manage the pollution impact of road traffic congestion. Unfortunately, the classic way to combat traffic congestion in Kuwait has been to increase the road capacity by adding new roads or lanes to the transport networks as opposed to reducing vehicle numbers [3].

To reduce the reliance on fossil fuels and mitigate greenhouse gas emissions, electric vehicles (EVs) have gained significant attention in recent years [5]. Globally, the number of EVs on the road exceeded more than 10 million by the middle of 2021, and this figure is expected to reach 120 million by 2030 [6,7]. This acceleration in sales is driven by many factors, including breakthroughs in lithium-ion battery technology, cost reductions and increasing range, stability and lifetime. These milestones, coupled with the drive to net zero, allowed many traditional vehicles manufacturers to enter the market, resulting in a cheaper and wider range of EVs to be commercially available [8]. In addition, such development reduced customers' anxiety, resulting in a higher number of EV technology adopters globally.

The harsh climatic conditions in Kuwait will have implications for the energy consumption of EVs and therefore will affect the provision of charging infrastructure. While a number of relevant studies were found in a review of the literature, the *real-world* performance of EVs in harsh environmental conditions, specifically in hot countries, remains little studied. In Liu et al. [5], for example, the maximum ambient temperature recorded was 37 °C, a temperature regularly exceeded by a large margin for many months of the year in countries such as Kuwait.

Previous literature overlooked the parameter affecting energy consumption in EVs related to the climate [5], even though ambient temperature has a significant effect. Literature of studied EV performance in warm to hot weather is limited [8]. In 2017, Taggart [8] used real-world fleet dataset from Tesla, Inc. covering over 10,000 individual vehicles, with an average trip distance of 22,000 miles per car. The study showed that energy consumption of EV driving is at the lowest level at moderate temperatures (20–30 °C), with the largest energy consumption for extreme cold (below the freezing point). The study illustrated that the average energy consumption over trip length is inversely related to trip distance. For instance, short trips (0–10 miles) noticeably incurred remarkably high energy comparison compared to trips over 25 miles. Dost et al. [9] monitored the behaviour of a representative sample of 500 people in Germany in a field test. Twenty-four electric cars were used to measure the parameters affecting energy consumption over 700,000 km. The work showed that high energy consumption (increased by 60%) related to driving in moderate wintry weather of 10 °C and highlighted the need to introduce more efficient heating air conditioning units in vehicles.

Yuksel and Michalek [10] tested the Nissan Leaf EV to develop a general functional relationship between ambient temperature and energy consumption efficiency. The research concluded that this EV uses 15% energy per mile related to weather data and found that yearly average energy consumption (per mile) for this type of EV is 15% higher in the relatively cold states in the USA compared to warmer states on the Pacific Coast. The paper relied on 7000 real-world trips, compared to a fixed estimation of the expected range of the Nisan Leaf's battery capacity of 21 kWh. This confirmed the sole relationship between differences in climate and energy utilisation. Liu et al. [5] modelled the effect of ambient temperature on EV energy consumption. The work emphasised the overexaggerated common concept that energy consumption in hot weather is extremely high, and vice versa. They considered the factors affecting energy consumption of EVs in a real-world field study and used GPS trajectory data for 68 EVs in Japan for 2 years up to January 2013. The research concluded that the most economic temperature to drive in is around 23 °C and observed that in high-energy-consuming trips, the heater and air conditioner are used simultaneously; thus, they recommended to automatically prevent the use of the two functions at the same time to prevent wasting energy. This work aims to provide additional empirical data on these effects by analysing real field data of an EV operating in high-temperature Kuwait.

Table 1 shows the average daily ambient air temperature in Kuwait, which is warm to extremely hot all year. The maximum average daily ambient air temperature varies between 39.5 °C in July and a minimum of 15 °C in December. The daytime temperatures are extreme in summer months, with a maximum average of 46 °C in July and August, and are mostly high at the time of coming back from work and school. During these times, in-vehicle air conditioning loads of cars working on fossil fuel could increase the energy consumption by up to 10% [11], especially on short trips with an average speed of less than 30 mph. Therefore, a significant concern for consumers purchasing electric cars in Kuwait is the relationship between hot temperature, energy intensity (the energy consumption per kilometre travelled) and the available range of an EV on a single charge.

Table 1. Average daily ambient air temperature in Kuwait, adopted from [1].

	January	February	March	April	May	June	July	August	September	October	November	December
All day (Avg. °C)	15	15.5	22	27	33	37.5	39.5	39	36	30	20.5	15
Night (Min. °C)	8	10	14	20	25	29	30	30	26	21	14	9
Day (Max. °C)	19	22	28	33	40	45	46	46	43	37	27	21

This study investigates the viability of utilising electrical vehicles (EVs) in the hot climate of Kuwait. We aim to contribute to knowledge and improve the understanding of temperature-related effects on the range of EVs under the hot and arid conditions encountered in Kuwait, but with implications for other similar climates around the world. The paper is organised as follows: the next section describes the methodology, followed by the data collection, the results and discussion and then the conclusions of the study.

2. Methodology

The statistical modelling presented in this study investigated the relationship between temperature and energy intensity, defined as the energy consumption per kilometre travelled. The modelling used ordinary least squares (OLS) regression to examine the relationship between ambient temperature recorded by the vehicle at the start of each journey and the energy intensity. The dependent variable, the average energy intensity for each trip (EI_i), is a measure of the electrical energy used to travel one kilometre. The metric was calculated from data collected for energy use at the start ($Estart_i$) and end ($Eend_i$) of each trip and the distance travelled (D_i), represented by Equation (1).

$$EI_i = \frac{(Estart_i - Eend_i)}{D_i} \quad (1)$$

In fitting the data of energy intensity against temperature, a number of polynomial models were used, and the model with the best balance between simplicity and explanatory power was selected. The model optimal relationship was a third-degree polynomial of the form ($y = \beta_0 + \beta_1 \cdot x + \beta_2 \cdot x^2 + \beta_3 \cdot x^3$), where y is the predicted energy intensity of a trip (in Wh/km) and x is the starting ambient temperature measured by the car (in degrees Celsius, °C). The model fit, coefficients (β_1, β_2, and β_3) and intercept (β_0) are reported in Section 4.

3. Data Collection and Description

As driving is linked with the daily activities of the residents in the country, the data should match various activities a typical Kuwaiti household may carry out. Considering the parameters that impact EVs' energy consumption, a Chevrolet Bolt EV–2019 car (Figure 1) was driven to simulate the five main trip scenarios in Kuwait: (i) home–office (morning), (ii) office–home (afternoon), (iii) peak hours (high traffic), (iv) short trips near home (late evening and night) and (v) long trips (random drives). The car used in the study has a range of 238 miles on a full charge, estimated by the Environmental Protection Agency in the USA (EPA) [12]. The Bolt EV's 60 kilowatt-hour (kWh) lithium-ion battery pack is made up of 288 individual cells. An available DC (direct current) fast charging system enables the battery to be charged to a range of up to 90 miles in 30 min. The car uses a

200 hp/150 kW permanent magnetic drive single motor and gear set [13,14]. Table 2 shows the specifications of the Chevrolet Bolt EV that was used in the study.

Figure 1. (**a**) Photograph of the test vehicle. (**b**–**d**) Vehicle status display showing information collected at beginning and end of each journey.

Table 2. The 2019 Chevrolet Bolt EV specifications.

Driving range efficiency:	238 miles on a full charge	**Motor type:**	Single motor and gear set. Permanent magnetic drive motor.
Battery system type:	Rechargeable energy storage system	**Power:**	200 hp/150 kW
Battery chemistry:	Lithium-ion	**Torque (lb-ft/Nm):**	266/360
Cells number:	288	**240 V charging time:**	9.5 h
Energy:	60 kWh	**DC Fast Charging time:**	Up to 90 miles in 30 min

Data collection of the use of the vehicle began in July 2019 and is ongoing. This research reports on the analysis of data collected between 1 August 2019 and 31 October 2021. It must be noted that this period included several months of government-mandated restrictions on activities and movements (e.g., curfews of varying lengths) of the population due the COVID-19 pandemic. Partial lockdowns, generally applied during the evening and overnight hours, were in operation from 22 March 2020 to 9 May 2020 and 31 May 2020 to 29 August 2020. A full lockdown was in operation between 10 May and 30 May 2020 and consisted of a 24-h curfew [15].

The vehicle user collected details for each journey manually. The date, time, vehicle odometer and temperature readings were recorded at the beginning and end of each journey alongside information from the vehicle status display, which contained information on the charge status of the vehicle battery, amount of energy used and ambient temperature measurement (Figure 1). The latter was measured using the standard measurement device installed by the vehicle manufacturer. While the sensor does not provide a reliable measurement of ambient conditions, it does provide a useful proxy measurement for the operating conditions at the start of the journey. The limitations of this method are acknowledged in Section 5. These details were recorded using photographs and subsequently entered into a data spreadsheet.

The data from the vehicle status display provided the following metrics, measured since the last time the vehicle was fully charged: energy used in kilowatt-hours, distance travelled in kilometres, proportion (%) of energy consumption used for driving, proportion (%) of energy consumption used for air conditioning and proportion (%) of energy consumption used for battery conditioning. From these measurements, the energy used (in kWh) and distance travelled (in km) were calculated for each trip. Disaggregating the total energy used into components for driving, air conditioning and battery conditioning was performed using the values for proportion of energy consumption recorded by the vehicle status screen. Standardised energy intensity was also calculated for each by dividing the energy used by trip distance, giving overall Watt-hours per kilometre (Wh/km) as well as disaggregated values for driving, air conditioning and battery conditioning.

Data Cleaning and Validation Checks

Any trip with missing odometer reading(s) (from either the start or end of the journey) was removed prior to analysis, leaving data from 2024 trips made on 577 days within the study period. The dataset contained two separate measurements for trip distance: (a) collected via the car's odometer reading, accurate to 1 km, and (b) collected via the distance shown on the vehicle status display, accurate to 0.1 km. Using these two measurements, it was straightforward to run a check for data entry errors. To check the quality of the data recorded, we inspected the correlation between the two measures of trip distance recorded in the dataset. The resulting scatter plot is shown in Figure 2.

We observe that, generally, the two measures are very closely correlated; data points appearing on the black line represent trips where the distance obtained from the odometer reading matches the distance obtained from the charging readings. The scatter plot shows several points plotted away from the line, indicating errors in data collection. We exclude data points that diverge from this line, using a tolerance of odometer distance $\pm$ 1% and $\pm$1 km (shown as red lines), as we have lower confidence that these data points are valid. This check removed 53 observations from the dataset.

Other validation checks were also performed to exclude observations with clear data entry errors. First, trips recorded with zero and negative distances were removed. Trips with erroneously long distances were also removed with a filter applied to exclude any trip recorded over 200 km. Trips with missing or erroneous start or finish times were also excluded. Finally, the energy use and calculated values for energy intensity were examined. Trips with negative values for energy use were excluded (six observations), along with trips with average energy intensity of greater than 500 Watt-hours per kilometre (eight observations). The remaining data contained 1822 trips recorded from 530 days.

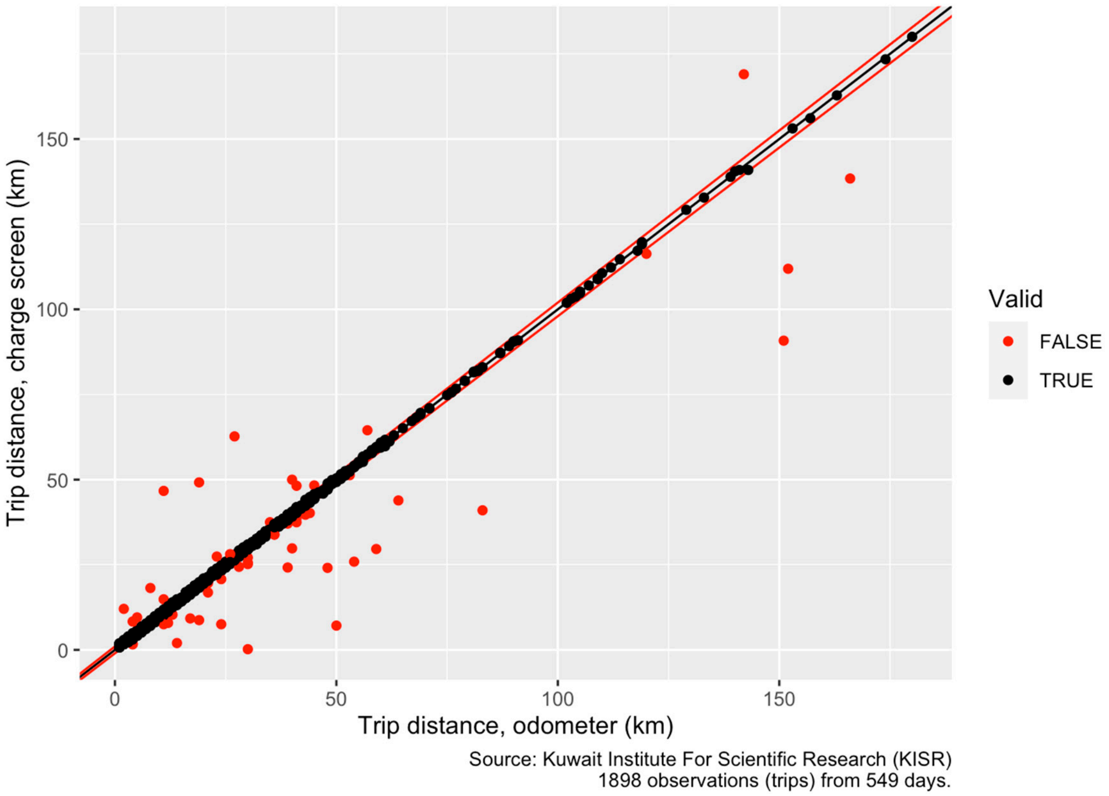

Figure 2. Scatter plot of recorded trip distances obtained through odometer and vehicle status screen. Black line indicates both measures equal, red lines indicate allowance for rounding and tolerance (odometer distance ± 1% ± 1 km). Points lying outside of tolerance are shown in red.

4. Results and Discussion

4.1. Descriptive Statistics

Table 3 shows a summary of the trips recorded by month following the initial cleaning of the data. The fewest trips were recorded in May and June 2020 (11–12 trips per month), a time when government COVID-19 restrictions and curfews were in place. The most trips during a single month were recorded in October 2020 (216 trips). Inspection of the average energy intensity shows that the highest values occur in the months of July and August, with average energy intensity of 165 Watt-hours per kilometre (Wh/km) or greater.

4.2. Temperature Measurement

Included in the data collected at the start and end of each journey was the ambient temperature measured by the car. While these measurements may not accurately reflect the ambient conditions, these measurements provide useful data about the operating temperature of the vehicle at the beginning and end of the journey. Figure 3 shows a scatter plot of recorded temperature at the start of each journey plotted against the time that the journey began. The vast majority of trips in the journey data (greater than 99%) started between 06:00 and 00:00. To provide greater clarity in the plot, nine observations (less than 0.5% of the trips) were removed from the plotted data, corresponding to trips with start times between 00:00 and 06:00 h. Furthermore, 12 observations were also removed due to missing temperature measurement. General trends in the data can be observed, showing that trips starting between 14:00 and 16:00 h show the highest recorded temperatures. The observations are grouped by month, with each month shown as a different colour on the chart, allowing the seasonal trend in recorded temperature to be identified. Inspection of the figure shows that the lowest starting temperatures are recorded in the months of December, January and February. The highest starting temperatures are recorded in the months of June, July and August.

Table 3. Summary of recorded car journeys by month. Figures in bold indicate data collected during periods when government-mandated restrictions (full or partial lockdown/curfew) were in place.

Month	Year	Trips (Number)	Total Distance (km)	Average Distance (km)	Energy Used (kWh)	Average Energy Intensity (kWh/km)
October	2019	45	1545	34.3	228.5	148
November	2019	24	876	36.5	120.0	137
December	2019	29	995	34.3	132.4	133
January	2020	57	1865	32.7	281.7	151
February	**2020**	**39**	**1651**	**42.3**	**237.5**	**144**
March	**2020**	**37**	**1051**	**28.4**	**143.0**	**136**
April	**2020**	**15**	**759**	**50.6**	**100.5**	**132**
May	**2020**	**12**	**433**	**36.1**	**58.9**	**136**
June	**2020**	**11**	**511**	**46.5**	**79.7**	**156**
July	**2020**	**23**	**1442**	**62.7**	**267.7**	**186**
August	**2020**	**25**	**1871**	**74.8**	**326.0**	**174**
October	2020	216	5174	24.0	763.4	148
November	2020	111	2141	19.3	279.9	131
December	2020	159	2863	18.0	377.0	132
January	2021	131	2620	20.0	339.7	130
February	2021	128	2791	21.8	350.9	126
March	2021	122	2919	23.9	363.5	125
April	2021	114	2458	21.6	322.2	131
May	2021	84	2166	25.8	308.1	142
June	2021	104	2485	23.9	394.0	159
July	2021	73	1830	25.1	308.7	169
August	2021	118	2527	21.4	415.7	165
October	2021	145	3139	21.6	461.1	147

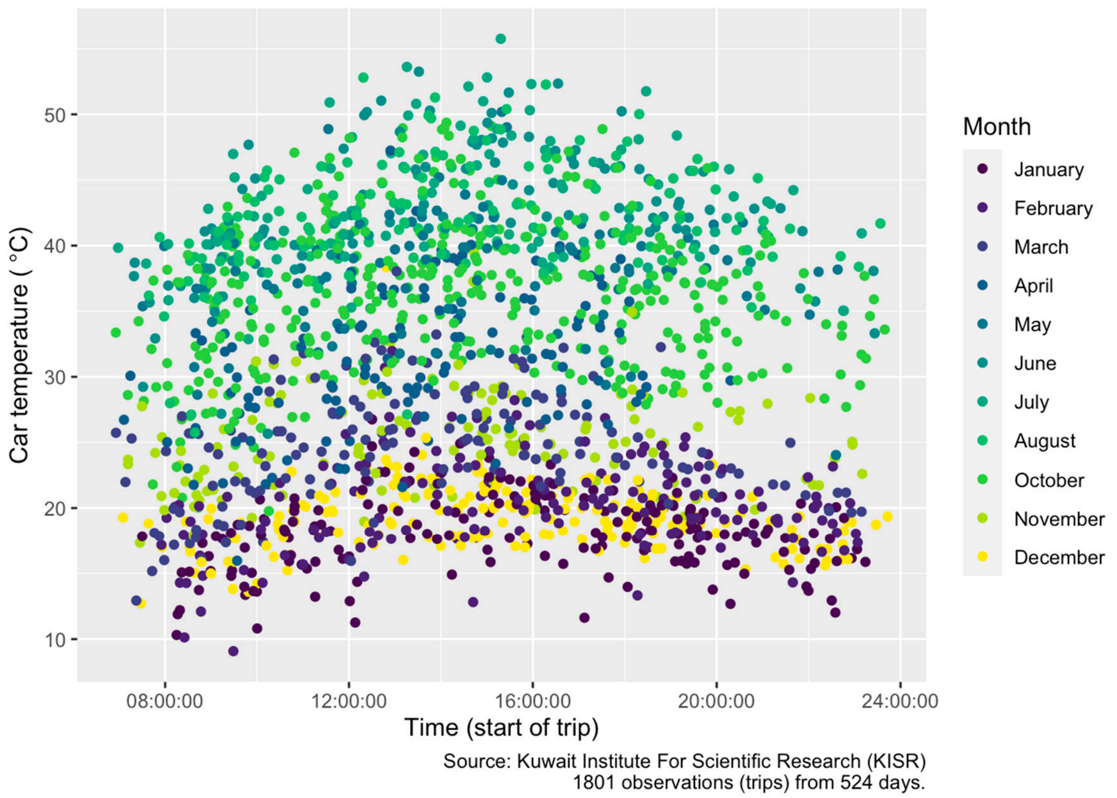

Figure 3. Scatter plot of recorded temperature measurements at the start of each journey against journey start time. Point colour indicates month of recorded journey.

The distribution of temperature recorded by the vehicle shown in Figure 4 reveals that for the use of the study vehicle, a large number of journeys begin with high car temperatures that are likely to affect the energy intensity. Approximately half of the recorded journeys in the dataset started with the car temperature at 30 °C or above and approximately a quarter at 40 °C or above. It is noted that the data collection period included dates where restrictions on movement were in place due to COVID-19, resulting in lower vehicle usage during summer months. As this may have had the effect of skewing the data, the distribution was examined for a period of one year, excluding the time when restrictions were in place.

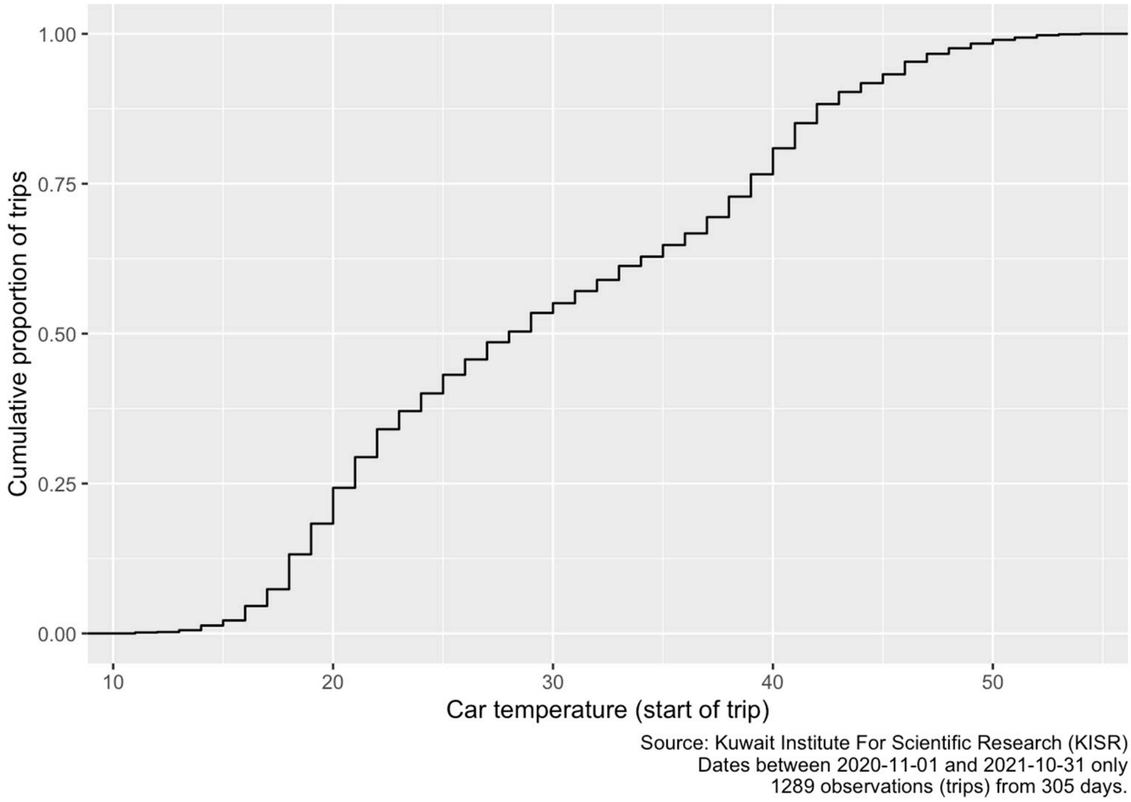

Figure 4. Cumulative distribution of trips by temperature, November 2020 to October 2021 only (avoiding period of COVID-19 restrictions).

4.3. Energy Use

As expected, energy use shows a strong positive correlation with distance travelled for each trip (Spearman correlation coefficient = 0.954, $p < 0.01$). This relationship is illustrated in Figure 5, showing a scatter plot of trip distance (in km) against energy used (kWh). The simple relationship described by the regression line gives an energy intensity of 150 Wh/km.

Turning to the relationship between energy consumption and temperature, energy consumption by trip is first normalised for distance, using the calculated standardised energy intensity measured in Watt-hours per kilometre (Wh/km). Figure 6 shows a scatterplot of car temperature at trip start, measured in degrees centigrade (°C) versus energy intensity. We observe a wider distribution of energy intensity as temperature increases. From the polynomial model fitted to the data, the relationship between (starting) temperature and energy intensity reaches a minimum of 130 Wh/km at 22.8 °C and supports the conclusion of the study by Liu et al. [5] in Japan finding the most economical temperature of 23 °C. Below 20 °C, we observe that energy intensity rises slightly with decreasing temperature, and above 25 °C, we observe that energy intensity rises with increasing temperature.

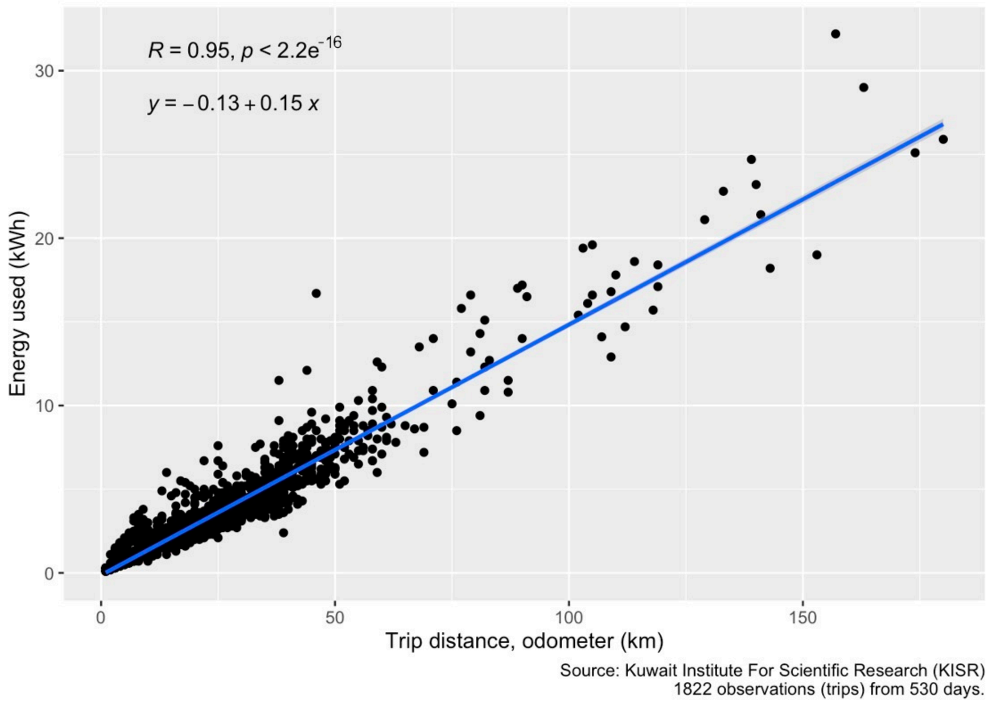

Figure 5. Electrical energy used against trip distance for each trip recorded.

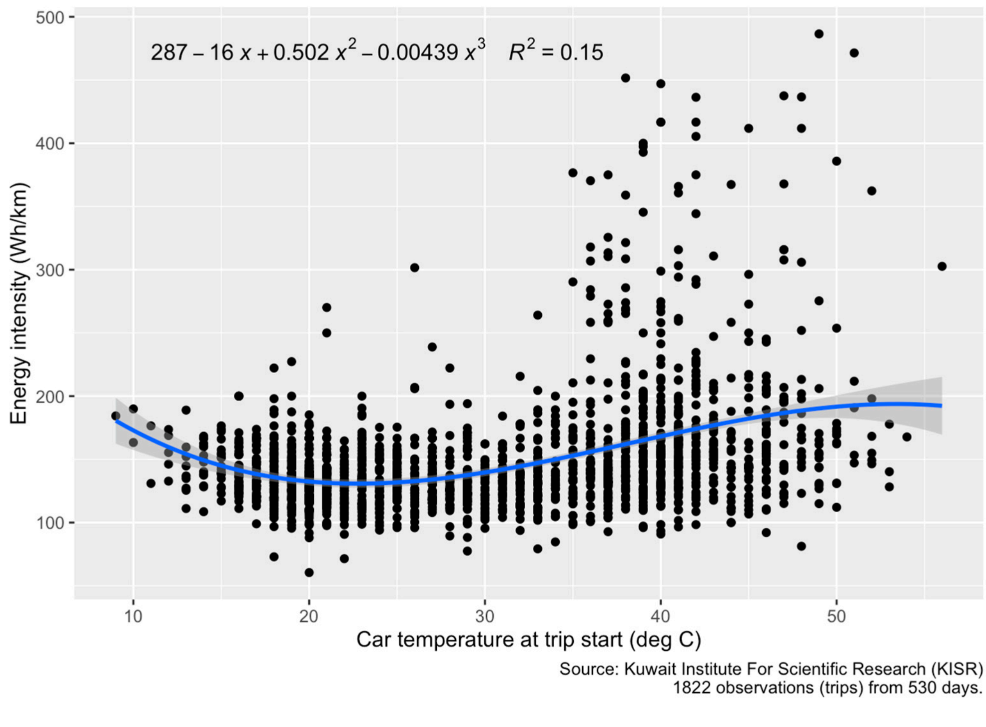

Figure 6. Energy intensity of trips against car temperature at start of journey. Fitted line is a third-degree polynomial.

As mentioned earlier, the data were fitted to a linear regression model using a third-degree polynomial. The model coefficients are shown in Table 4, showing that all terms are statistically significant. This model was chosen over other polynomial models tested as it optimised model fit against model complexity. The third-degree polynomial model achieved an improved model fit compared to the second-degree model with an adjusted R^2 value of 0.149 (versus 0.141). The model fit was not significantly improved by using fourth- or fifth-degree polynomial models (adjusted R^2 = 0.149 and 0.150, respectively). The lower number of journeys recorded at the limits of the temperature distribution, below 15 °C and above 45 °C, reduce model performance.

Table 4. Model coefficients (and confidence intervals).

	Dependent Variable:
	Y
β_1	−16.025 ***
	(−21.833, −10.217)
β_2	0.502 ***
	(0.313, 0.691)
β_3	−0.004 ***
	(−0.006, −0.002)
Constant (β_0)	287.313 ***
	(231.328, 343.298)
Observations	1809
R^2	0.151
Adjusted R^2	0.149
Residual Std. Error	44.100 (DF = 1805)
F Statistic	106.733 *** (DF = 3; 1805)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The model was used to estimate the range reduction, in percent, at car temperatures between 10 °C and 50 °C. Range reduction was calculated by dividing the minimum modelled energy intensity by the energy intensity at given car temperatures. The modelled in-use energy intensities (in Wh/km) are shown in Table 5 and Figure 7 alongside estimated range reductions (expressed as a percentage) for car temperatures at five-degree intervals (Figure 7, right-hand axis).

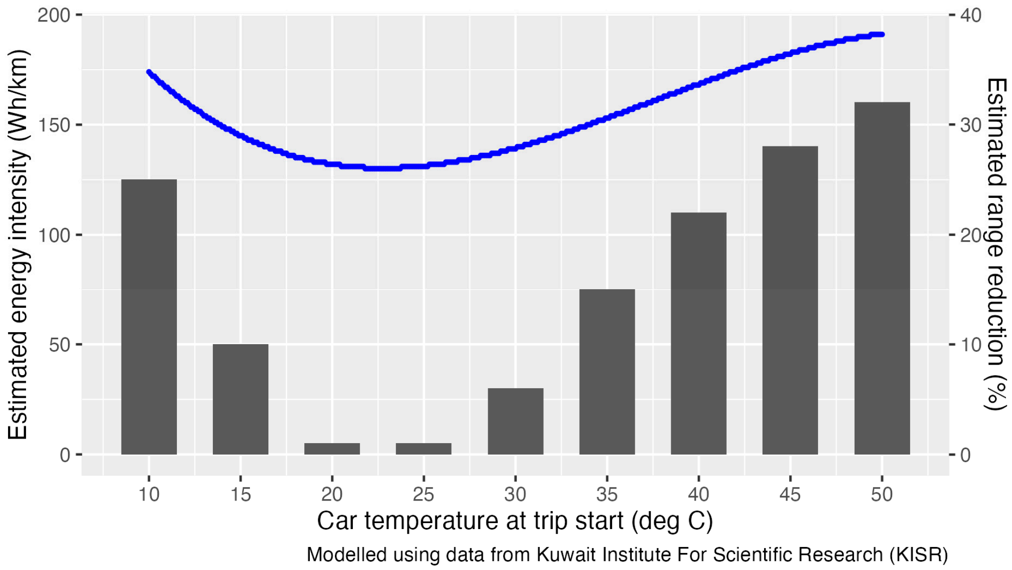

Figure 7. Modelled in-use energy intensity (blue line, left axis) and range reduction (grey columns, right axis) by car temperature at start of journey.

Using the assumption that the range of the vehicle is directly proportional to the in-use energy intensity, when the starting temperature of the car is below 20 °C and above 25 °C, the model results show that energy intensity increases, and estimated vehicle range reduces accordingly. The selected model shows (Table 5 and Figure 7) that at a starting temperature of 30 °C, the vehicle range would be decreased by 6%. The reduction in range increases with increasing starting temperature, with a 22% reduction at 40 °C and a 32% reduction at 50 °C. Similarly, range decreases at starting temperatures below 20 °C, resulting in a 10% reduction at 15 °C, rising to a 25% reduction at 10 °C. These findings of increased energy use in moderately cold driving conditions are not as sizable as those found by Dost et al. [9] in their German study and are comparable to those found in the United States by Yuksel and Michalek [10].

Table 5. Modelled in-use energy intensity and range reduction by car temperature at start of journey.

Car Temperature at Start of Journey (°C)	Energy Intensity (Wh/km)	Estimated Range Reduction (%)
10	174	25
15	145	10
20	132	1
25	131	1
30	139	6
35	153	15
40	168	22
45	182	28
50	191	32

5. Conclusions, Limitations and Future Work

This research investigated the impact of high ambient temperatures on vehicle efficiency from journeys made in a region with higher ambient temperatures (>50 °C) compared to those recorded by Liu et al. [5] (<35 °C). It presents empirical data collected through real-world usage of a single electric vehicle in Kuwait under environmental conditions that would be expected under typical use in the country. As would be expected, the data show a strong correlation between journey distance and energy use. Modelling of the data also shows a significant relationship between the car temperatures recorded at the start of journeys with the measured average energy intensity for journeys.

The results gained in this real-world vehicle in use case study (in contrast to lab conditions) indicate that there is a significant efficiency penalty when driving the EV in the hot conditions experienced in Kuwait and that hot conditions are common for journeys encountered. This has implications for EV range in such climates and is important in relation to customer perception—more specifically, travel range anxiety. The reduction in range resulting from increased energy intensity of use in higher temperatures also has implications for charging infrastructure.

Due to the unreliability of the disaggregated energy use of different systems within the vehicle, it was not possible to directly investigate the contribution of air conditioning or battery conditioning to the increase in energy intensity at higher temperatures. Nevertheless, the results show that energy intensity increases with temperature measured by the EV at the start of journeys. However, how much of the increased energy intensity is attributable to driver and passenger comfort preferences and to the response of vehicle performance to operating temperature cannot be ascertained from this study. Directly monitoring the energy consumption of these systems in the future would provide valuable data with which to further investigate the components of the temperature effect found in this case study. Combined with further instrumentation of the cabin (e.g., temperature and humidity measurement) and more detailed measurements of ambient environmental conditions, such data would allow some disentanglement of the cause of temperature effects on vehicle energy intensity due to vehicle performance and/or passenger comfort preferences.

While the ambient temperature measured by the car provides an indication of the operating conditions of the vehicle during each journey, it does not provide detailed information on the ambient conditions both prior to, and during, operation. Further investigation is required to understand the effect of different vehicle storage and parking arrangements on the relationship between ambient temperature, car operating temperatures and cabin conditions, and by extension, energy intensity and vehicle range. For example, carpark shading and/or cabin pre-cooling while charging would decrease cabin temperatures at journey start, reducing the energy demand for air conditioning and thereby improving energy intensity and increasing range. Such measures may also improve driver and occupant comfort.

Providing further measurements of vehicle driving parameters (such as speed, acceleration) and route information (such as road type, gradient [16]) would allow future work to investigate and control for variables related to road conditions, traffic and driving style.

Author Contributions: Overall research concept, H.H.; conceptualisation, T.R., M.M. and A.S.B.; methodology, T.R. and M.M.; software, T.R.; formal analysis, T.R. and M.M.; investigation, H.H. and T.R.; resources, H.H. and A.S.B.; data curation, T.R. and H.H.; writing—original draft preparation, H.H., T.R. and M.M.; writing—review and editing, A.S.B., M.M. and T.R.; visualisation, T.R. and H.H.; supervision, H.H. and A.S.B.; project administration, H.H.; funding acquisition, H.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Kuwait Foundation for the Advancement of Sciences through project number EA084C awarded to the Kuwait Institute for Scientific Research (KISR).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors acknowledge the Kuwait Institute for Scientific Research (KISR) for funding received to support this research. This work is also part of the activities of the Energy and Climate Change Division and the Sustainable Energy Research Group in the School of Engineering at the University of Southampton (www.energy.soton.ac.uk, accessed on 29 March 2022), U.K.

Conflicts of Interest: The authors declare no conflict of interest.

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