Efficiency Contingency Factors for Commercial EVs Optimal Centralized Charging Stations

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***Abstract*— This paper provides an Optimal Centralized Charging Station (OCCS) mechanism using an Optimal Commercialized Demand Response (OCDR) program coupled with three efficiency contingency factors (i.e., rolling resistance, aerodynamic drag, and traffic flow inertia) that are faced by commercial EVs. Additionally, this paper provides a detailed formulation for the optimal number of level chargers that can accommodate the system of operations for commercial and logistic businesses (CLBs). The methodology proposed contributes to curtail EV charging traffic congestion as well as shedding the load to avoid excess amount of charging loads. In this paper, three contingency factors are thoroughly examined by OCCS combined with OCDR for four case studies: high efficiency contingency, average efficiency contingency, low efficiency contingency, and ideal efficiency case studies. The results of the proposed methodology show an increase OCCS cost by approximately 141% and optimal number of charge level utilized.**

***Index Terms*—Commercial electric vehicles (EVs), efficiency contingencies, optimal centralized charging station (OCCS), optimal commercialized demand response (OCDR).**

I. Introduction

Commercial EVs promote as a promising opportunity to minimize CO_2 emissions, combat climate change, and minimize fossil fuel dependency [1], [2]. However, major battery advancements, substantial maintenance savings, and government incentives for EV battery technology have curtailed the proliferation of commercial EV market growth [3]. Nevertheless, it is expected that by 2024 commercial EVs will contribute to the vehicle marketplace in four categories: long-haul trucks, short-haul trucks, city delivery trucks, and heavy-duty (HD) pick-up trucks [3]. Moreover, the new emergence of long-haul and short-haul truck EVs is set to roll out in the vehicle market by the start of 2023 [4].

Alongside the increased growth of EVs and the emergence of commercial EVs, the global EV charging station is projected to grow significantly in the upcoming years [4]. Hence, the lack of an EV charging station management system is a significant issue invoking time-consumption drawbacks, complex charging processes, high power consumption, and untenable EV charging traffic congestion [5]. Moreover, no research paper has attributed to the optimization of commercial EV charging station management nor tackled the preceding growing challenges of commercial EV charging needs and load growth.

Most papers propose complex forecasting models and demand response systems with impatient leave scenarios to overcome EV charging station challenges [6]-[8]. However, many of these papers only account for commuter EVs charging behavior and battery characteristics, which have shorter charging times than commercial EVs. Commercial vehicles driving and fueling behavior is notably different from commuter vehicles, as they are bound to the CLBs system of operation scheduling [9], [10]. Moreover, these commercial vehicle behaviors can be visualized in present segregated diesel refueling stations for commercial vehicles to appropriate their fueling time constraint needs [10]. In previous work, an optimized commercial EV charging station demand response was formulated, which convolutes a load-shedding charging solution, EV charging traffic congestion curtailment, and CLBs system of operation needs standards appropriation [11]. However, this research paper will implement and examine efficiency contingency factors that commercial EVs face as these factors increase charging and driving range demand needs.

Notably, many of these distributed energy resources (DERs) are constrained to an efficiency contingency factor that reduces performance output. Therefore, it is necessary to account for the vehicular efficiency contingency factors faced by commercial EVs that constrain driving range performance. Commercial vehicles are faced with various environmental efficiency contingency mileage losses when driving. These vehicle efficiency contingency factors are rolling resistance, aerodynamic drag, and traffic flow inertia [12], [13]. These factors are greatly enhanced in commercial EV driving as they are curtailed by high gross weight loads and large vehicle sizing [13], [14]. Vehicular driving efficiency contingency factors in commercial EVs are not appropriated or implemented in typical EV charging optimization. However, these efficiency contingency factors play a considerable role in increasing charging demand needs as more EVs are on the road and curtailed by charging time constraints, such as commercial EVs [13].

This paper proposes an optimal demand response management system with efficiency contingency factors for the precedented commercial EV technologies. Furthermore, tailoring to the system of operation needs of CLBs, EV load curtailment necessities of power system operators, and overcoming battery efficiency contingency losses in commercial EVs when driving. To determine the optimal

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number of level chargers needed for a CLB OCCS with an OCDR formulation through four efficiency contingency case studies, three-level charge levels 1, 2, and 3, power output and cost data characteristics as the current average level charger characteristics available in the market are implemented [15]. Then, through the appropriate selection and gathering of the commercial EV battery, haul, and physical input data characteristics by utilizing the prevalent upcoming commercial EVs through the manufacturer website and the haul, sizing, and efficiencies regulations through government-affiliated reports [16]-[22]. Followed by the total efficiency contingency factor formulation from three main efficiency contingencies to account for in commercial EV driving [12], [13]. The advantages of the proposed method over existing techniques are: (1) Provides an optimal commercial EV charging station solution with efficiency factors implemented; (2) Evaluates four levels of efficiency factors faced when driving; (3) Load sheds excess level charger loads; and (4) Applicable to CLBs as it abides by its system of operation standards.

The structure of the paper is as follows. Section II provides the input commercial EV and Level charger data selection. Followed by the total efficiency factor formulation and the OCCS with contingency factors for commercial EV methodology in Section III and IV. Then, the case study and results through a parameter algorithm-based optimization model are represented in Section V, followed by the conclusion in Section VI.

II. Input Commercial EV and Level Charger Data Selection

This section provides the formulation and selection of anticipated commercial EV and level charger input data characteristics with its respective variables. Section A is the collection of level charger power output and cost data. Followed by accumulation of the commercial EV input data battery, hauling, and physical data characteristics in Section B.

A. Level Charger Data Selection

The level charger data selection is formulated by the average power output and cost data characteristics of three sets of level chargers available in the marketplace [15]. The level charger data characteristics with their respective variables is represented in Table I.

TABLE I. Level Charger Data Characteristics with its Respective Variables

(m)	1	2	3
Charger Level (l_m)	Level 1	Level 2	Level 3
Power Output (p_m)	7 kW	17 kW	203 kW
Level Charger Cost (c_m)	\$210	\$775	\$23,500

B. Commercial EV Data Selection

The commercial EV data characteristics with their respective variables are represented in Table II and are formulated by the utilization of anticipated commercial EVs upcoming in the market split into four categories [3]. The commercial EV chosen is as follows: the Tesla 500 Mile Semi for the long-haul truck, Tesla 300 Mile Semi for the short haul truck, Brightdrop Zevo 600 for the city delivery truck, and Tesla Tri Motor Cybertruck for HD pick-up truck. The four commercial EV categories are attributed to the selection and gathering of the commercial EV respective data characteristics and variable selection split into three sections: commercial EV battery data, commercial EV haul data, and commercial EV physical data.

TABLE II. Commercial EV Data Characteristics with its Respective Variables

(n)	1	2	3	4
Commercial EV (x_n)	Tesla 500 Mile Semi **(Long Haul Truck)**	Tesla 300 Mile Semi **(Short Haul Truck)**	Brightdrop Zevo 600 **(City Delivery Truck)**	Tesla Tri-Motor Cybertruck **(HD Pick-up Truck)**
Commercial EV Battery Data				
Battery Capacity ($b_n max$)	100 kWh	600 kWh	165 kWh	200 kWh
Range ($r_n max$)	804 km	483 km	402 km	804 km
Mileage (m_n)	0.5 mi/kWh	0.5 mi/kWh	1.52 mi/kWh	2.5 mi/kWh
Efficiency (e_n)	90%	90%	90%	90%
Brake Efficiency (eb_n)	97 %	97%	97%	97%
Acceleration (a_n)	0.5 m/s^2	0.5 m/s^2	0.5 m/s^2	0.5 m/s^2
Commercial EV Haul Data				
Vehicle Weight (Wv_n)	12,701 kg	10,247 kg	3,538 kg	2,835 kg
Tailer Weight (Wt_n)	4,536 kg	4,536 kg	0 kg	907 kg
Haul Weight (Wh_n)	19,958 kg	20,412 kg	907 kg	2,608 kg
Total Gross Weight (TW_n)	37,195 kg	37,195 kg	4,536 kg	6,350 kg
Commercial EV Physical Data				
Vehicle Drag Coefficient (c_n)	0.36	0.36	0.32	0.38
Drag Coefficient With Trailer (cp_n)	0.36	0.36	0.32	0.48
Frontal Surface Area With Haul (A_n)	10.67 m^2	10.67 m^2	6.01 m^2	4.06 m^2
Coefficient of Rolling Resistance (Crr_n)	.006	.006	.001	.006

In Table I, the EV battery capacity, range, mileage, total gross weight, and vehicle drag coefficients are obtained through the vehicle manufacturer's website, followed by the Tesla Cybertruck and Brightdrop Zevo 600 vehicle weight [16], [17]. Next, the efficiency, brake efficiency, and

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acceleration are gathered from the computational assumption by the Environmental Protection Agency (EPA) automotive power trend of EVs [18]. The commercial EV vehicle weight of the Tesla semis, trailer weight, haul weight, drag coefficient with trailer, and frontal surface with haul is formulated by associating a trailer from the Department of Transportation (DOT) truck and trailer regulations [19]. The Tesla Semis are entailed to a class eight 53-foot dry van trailer, the Brightdrop Zevo 600 with no trailer, and the Tesla Cybertruck to a class three 7 x 14 flatbed trailer with its associated average trailer weight and allowed haul weight [19]. Next, the Tesla Semis vehicle weight assumption is computed by deducting the trailer and haul weight from the total gross weight stated by Tesla and the Federal Highway Administration for class eight EV vehicles [19], [20]. Furthermore, the Tesla 500 Mile Semi is renounced to a lowered allowed haul weight limit to attribute the larger battery capacity in its vehicle weight limit compared to the Tesla 300 Mile Semi allowable load weight. The frontal surface area and drag coefficient of the Tesla Semis with haul and Brightdrop Zevo 600 are obtained from the manufacturer's website [17], [20]. Moreover, the Tesla Cybertruck values are assumed by a computational analysis from the truck height and trailer width dimensions with load characteristics from the Tesla website and DOT trailer regulations [16], [19]. The coefficient of rolling resistance is obtained from the Minnesota DOT rolling resistance study through an average estimation of the associated vehicle class [21].

III. Total Efficiency Contingency Factor Formulation

This section is the formulation of the total efficiency factor from the convolution of the three main efficiency contingency factors that commercial vehicles encounter: rolling resistance, aerodynamic drag, and traffic flow inertia [12], [13]. The section is constructed by the equation formulation of the rolling resistance, aerodynamic drag, and traffic flow inertia factors represented in Sections A, B, and C, followed by Section D, the total efficiency contingency factor formulation.

A. Rolling Resistance Factor

The rolling resistance factor is attributed to the frictional road surface roughness, slope grade, and gravitational forces acting against the longitudinal movement of the vehicle [11], [12]. The rolling resistance factor equation is defined as:

$$RF_{n.e} = (Crr_n * TW_n * g * V_{n.e}) + (an_{n.e} * TW_n * g * V_{n.e} * tr_{n.e}) \quad , \quad (4)$$

where $RF_{n.e}$ is the rolling resistance factor composed of TW_n represented as the total gross weight of the commercial EV, $V_{n.e}$ as the commercial EV average velocity, $an_{n.i}$ as the incline slope angle, and $tr_{n.e}$ as the percentage of road grade. With the addition of g represented as the gravity constant and Crr_n as the coefficient of rolling resistance. Moreover, each is associated with their respective commercial EV (n) and case study (e) characteristics.

B. Aerodynamic Drag Factor

The aerodynamic drag factor is attributed to the external wind frictional force opposing the directional movement of the vehicle [12], [13]. The aerodynamic drag factor equation is defined as:

$$AF_{n.e} = (\tfrac{1}{2} * Cd_n * A_n * (V_{n.e} + Vw_{n.e})^3 \quad , \quad (5)$$

where $AF_{n.e}$ is the aerodynamic drag factor composed, A_n represents the front surface area with haul, and Cd_n as the drag coefficient. Followed by ρ as the wind density constant, $Vw_{n.e}$ as the wind speed, and $V_{n.e}$ as the commercial EV average velocity. Moreover, each is associated with their respective commercial EV (n) and case study (e) characteristics.

C. Traffic Flow Inertia Factor

The traffic flow inertia factor is associated to the traffic contingencies of decelerations and accelerations attributable from city and highway driving efficiencies from the Environmental Protection Agency (EPA) [13], [18]. The traffic flow inertia factor equation is defined as:

$$Ea_{n.e} = (a_n * Empg_{n.e}) \quad , \quad (6)$$

$$TI_{n.e} = (\tfrac{1}{2} * TW_n * V_{n.e} * Ea_{n.e}(\tfrac{1}{e_n} - e_n * eb_n)) \quad , \quad (7)$$

where $TI_{n.e}$ is the traffic flow inertia factor composed of TW_n represented as the total weight of the commercial EV, $V_{n.e}$ as the commercial EV average velocity, and $Ea_{n.e}$ as the acceleration efficiency factor. Followed by the e_n represented as the commercial EV efficiency and eb_n as the commercial EV braking efficiency. The acceleration efficiency factor equation ($Ea_{n.e}$) is composed of a_n represented as the acceleration variable and $Empg_{n.e}$ as the miles per gallon equivalent (MPGe) efficiency. Moreover, each is associated with their respective commercial EV (n) and case study (e) characteristics.

D. Efficiency Contingency Factor Formulation

The total efficiency contingency factor formulation is convoluted through the efficiency contingency energy capacity equation from the construction of the three efficiency factors: rolling resistance factor, aerodynamic drag factor, and traffic flow inertia factor. The efficiency contingency energy capacity equation is defined as:

$$EC_{n.e} = (\frac{AF_{n.e} + RF_{n.e}}{e_n} * TI_{n.e}) * (\frac{r_n max}{V_{n.e}} * \omega) \quad , \quad (8)$$

where $EC_{n.e}$ is the efficiency contingency capacity needed to overcome all three efficiency factors. Furthermore, the equation is composed of $RF_{n.e}$ represented as the rolling resistance factor, $AF_{n.e}$ as the aerodynamic drag factor, and $TI_{n.e}$ as the traffic flow inertia factor. Followed by e_n represented as the commercial EV efficiency, $r_n$max as the max battery range of the commercial EV, $V_{n.e}$ as the commercial EV average velocity, and ω as the energy per work constant in kilowatt hour per joule. Moreover, each is associated with their respective commercial EV (n) and case study (e) characteristics. The formulation of the efficiency contingency factor is defined as:

$$ECF_{n..m.e} = b_{n.m}/EC_{n.e} \quad , \quad (9)$$

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where $ECF_{n.m.e}$ is the total efficiency contingency factor composed of $b_{n.m}$ represented as the battery capacity of the commercial EV associated level charger and $EC_{n.e}$ as the efficiency contingency energy capacity. Moreover, each is associated with their respective commercial EV (n), case study (e) and level charger (m) characteristics.

IV. OCCS with Efficiency Contingency Factors for Commercial EVs Methodology

The efficiency contingency factors with OCCS for commercial EVs is formulated with the utilization of previous work, OCCS with an OCDR methodology [11]. Moreover, implementing the total efficiency contingency factor through the parameter-bound optimization algorithm model of OCCS with an OCDR methodology. The total efficiency contingency factor implementation is executed through the battery computational characteristics computation within the algorithm model, as shown in Fig. 1.

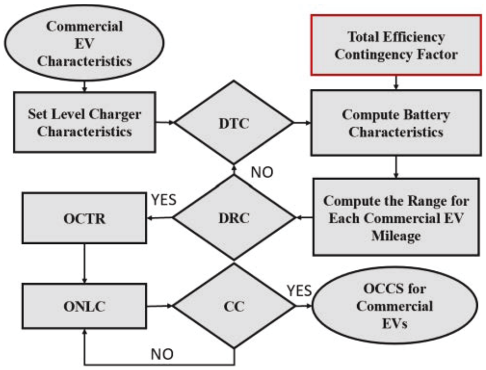

Fig. 1. OCCS with efficiency contingency factors flow chart diagram.

V. Case Study and Results

To analyze the impact of efficiency contingency factors through an OCCS with an OCDR formulation of a CLB. A convolution of four case studies will be conducted, which follows as high, medium, low, and ideal efficiency contingency cases. The input case duty data is represented in Section A, defining the CLB parameters and efficiency contingency characteristics, followed by Section B results and discussion of the four case studies.

A. Input Case Study Data

The parameter constraints and efficiency contingency input data are represented in Table III and IV. With its correspondent case study, commercial EV, and level charger variable.

TABLE III. OCDR Parameter Constraints Input Data

Total Number Of Commercial EVs (X_n)	Commercial Set EV (x_n)	Dispatch Time Constraint ($0 < ct_{n.m} \leq ct_n max$)	Desired Range Constraint ($r_n min \leq r_{n.m} \leq r_n max$)	Cost Constraint ($0 < \sum tc_i \leq TCmax$)
5	Tesla 500 mi Semi (x_1)	$0 < t_1 \leq$ 900 min	250 km $\leq r_1 \leq$ 804 km	\$0 < $\sum tc_i \leq$\$250,000
4	Tesla 300 mi Semi (x_2)	$0 < t_2 \leq$ 720 min	200 km $\leq r_2 \leq$ 483 km	
4	Brightdrop Zevo 600 (x_3)	$0 < t_3 \leq$ 280 min	120 km $\leq r_3 \leq$ 402 km	
3	Tesla Tri-Motor Cybertruck (x_4)	$0 < t_4 \leq$ 180 min	120 km $\leq r_4 \leq$ 804 km	

In Table III, the OCDR parameter constraints are formulated by the average system of operation needs of the correspondent vehicles of CLBs with a randomized number of commercial EVs.

TABLE IV. Efficiency Contingency Case Study Input Data

(n)	1	2	3	4
(e)	**High Efficiency Contingency Case Study (1)**			
Incline Slope ($an_{n.e}$)	10 %	10 %	10 %	10 %
Road Grade (tr_n)	1 %	1 %	1 %	1 %
Average Velocity ($V_{n.e}$)	29.1 m/s	29.1 m/s	29.1 m/s	29.1 m/s
Wind Speed ($Vw_{n.e}$)	4.47 m/s	4.47 m/s	4.47 m/s	4.47 m/s
City MPGe. Efficiency ($Empg_{n.e}$)	1.67	1.67	1.67	1.67
(e)	**Average Efficiency Contingency Case Study (2)**			
Incline Slope ($an_{n.e}$)	5 %	5 %	5 %	5 %
Road Grade (tr_n)	1 %	1 %	1 %	1 %
Average Velocity ($V_{n.e}$)	29.1 m/s	29.1 m/s	29.1 m/s	29.1 m/s
Wind Speed ($Vw_{n.e}$)	2.24 m/s	2.24 m/s	2.24 m/s	2.24 m/s
Average MPGe. Efficiency ($Empg_{n.e}$)	1.54	1.54	1.54	1.54
(e)	**Low Efficiency Contingency Case Study (3)**			
Incline Slope ($an_{n.e}$)	3 %	3 %	3 %	3 %
Road Grade (tr_n)	1 %	1 %	1 %	1 %
Average Velocity ($V_{n.e}$)	29.1 m/s	29.1 m/s	29.1 m/s	29.1 m/s
Wind Speed ($Vw_{n.e}$)	0.67 m/s	0.67 m/s	0.67 m/s	0.67 m/s
Highway MPGe. Efficiency ($Empg_{n.e}$)	1.5	1.5	1.5	1.5
(e)	**Ideal Efficiency Contingencies Case Study (4)**			
Incline Slope ($an_{n.e}$)	0 %	0 %	0 %	0 %
Road Grade (tr_n)	0 %	0	0	0
Average Velocity ($V_{n.e}$)	29.1 m/s	29.1 m/s	29.1 m/s	29.1 m/s
Wind Speed ($Vw_{n.e}$)	0 m/s	0 m/s	0 m/s	0 m/s
MPGe. Efficiency ($Empg_{n.e}$)	0	0	0	0

In Table IV, the incline slope, road grade, and average velocities are formulated by utilizing the average road constraint characteristics of the U.S [19]. The wind speeds are portioned equally throughout the contingencies case studies by the average wind speed in the U.S [20]. Moreover, the MPGe efficiency is attributed to the city and highway efficiency MPG loss for EVs formulated by the EPA [16].

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B. Results and Discussion

The formulation of the four case studies through the OCCS with an OCDR methodology is represented in Table V. This is done by integrating the correspondent total efficiency contingency factor formulated from the four case studies' input data within the algorithm model for each respective commercial EV. Moreover, utilizing the OCDR parameter constraints input data consistently throughout the four efficiency contingency case studies for each correspondent commercial EV.

TABLE V. Case Study Results and Data

OCCS with Efficiency Contingency Case Study	Level 1 Charger	Level 2 Charger	Level 3 Charger	Total Cost	OCDR Cost Constraint Validation	Total Average Efficiency Contingency Factor
(1) High Efficiency Contingency	0	3	13	$307,825	NO	46.75 %
(2) Average Efficiency Contingency	0	3	13	$307,825	NO	54.23 %
(3) Low Efficiency Contingency	0	4	12	$285,100	NO	59.52 %
(4) Ideal Efficiency Contingency	0	7	9	$216,925	YES	0 %

The case study results obtained from the algorithm model represent the OCCS optimal combination of level chargers with its correspondent total cost, OCDR cost constraint validation, and total average efficiency contingency factor from all four commercial EVs. The ideal efficiency case prompted as the only efficiency case to validate all the CLB system of operation needs with a total cost of $33,075 underneath the $250,000 cost margin. Furthermore, the low efficiency case over validates the cost constraint by $35,100 compared to the average and high efficiency case by $57,825. This total cost over-validation of the low efficiency case is attributed to a 59.52% total efficiency factor, whereas the average and high efficiency cases are at 54.23% and 46.75%.

VI. Conclusion

This paper implemented efficiency contingencies for commercial EVs through an OCCS with an OCDR methodology model. Implementing an amalgamation of three main efficiency contingency factors encountered in everyday commercial vehicles, rolling resistance, aerodynamic drag, and traffic flow. To convolute an appropriated load shedding solution of an optimal number of level chargers and reliable charging station management structure for commercial EVs by considering the system of operation needs of the CLB accounting commercial EV efficiency losses. Furthermore, it demonstrates the effects of optimizing level charger combinations and cost through a set of four case study scenarios, high, medium, and ideal efficiency contingency cases, through a CLB OCDR parameter case. Future work may involve implementing a short-term and long-term power grid load analysis of the proposed OCCS with efficiency contingencies through a full, partial, and idle charging connection case scenario.

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