Scheduling Electrified Freight Transportation to Increase Renewable Generation Utilization

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***Abstract*—A target has been set to have 100% carbon pollution-free electricity by the year 2035 in the US, requiring an increased reliance on renewable sources. However, as renewable energy sources become more integrated into power systems it causes a fluctuation in power supply. Batteries are typically used to deal with fluctuations but are unsuitable for longer timescales due to the associated costs. As of now, electric freight transportation is in the early stage of deployment. This paper presents a solution to help mitigate the challenge associated with renewables and reduce the variation in supply by leveraging the flexibility of supply chains and integrating electrified supply chains into power systems planning and operation. We demonstrate that (unlike batteries) supply chain flexibility can increase utilization of renewables, for incentives as low as $0.01 per MWh.**

I. Introduction

To meet the US renewable policy goal to have 100% zero-carbon electricity by 2035 will require a significant increase in renewable energy generation [1]. However, a major drawback of renewables is the fluctuation in the power supply, leading to challenges balancing the demand and supply for power [2]. Renewables, such as solar and wind power, are dependent on weather leading to them being stochastic in nature. It is also important to note that, although variation in power supply becomes smaller at lower time resolutions, it is still significant for longer periods such as a week.

Often batteries are used to smooth the fluctuations in renewable production and help minimize the difference between demand and supply of electricity [3]. However, batteries are not cost-competitive for storing energy for long periods of time. A breakdown of the cost of implementing a battery energy storage system can be seen in [4]. Batteries are useful for shorter time frames such as a day, but are not suitable for time frames greater than a month. A variety of energy storage technologies have been developed, and [5] shows a breakdown of their uses and effectiveness in dealing with the fluctuations of renewable energy – including discussing the importance of lowering the cost for energy storage technologies to increase the renewable energy utilization.

To deal with the fluctuations of renewable energy over longer time frames, cross-seasonal load shifts from industrial sectors has been analyzed. Cross-seasonal load shift aims to shift the production of goods to a season where electricity prices are lower, which is typically also where there is a larger production of renewable energy. In the case of solar power, it typically has a larger production from May to September in the Northern Hemisphere. However, cross-seasonal load shift only works for specific industry sectors that can shift production without major disruptions and additional costs [6].

Moreover, there is a significant body of research on the issues and solutions of integrating renewable energy into the grid, such as [7], which explores possible solutions such as storage devices and transmission grid expansion. Meanwhile, [8] addresses some solutions based on new technology that can be implemented and offloading power usage to lower peak times. It also highlights the high cost of using batteries to deal with fluctuations, particularly battery energy storage systems (BESS).

The paper will investigate an alternate solution to deal with the fluctuation in renewable resources, by leveraging the flexibility of future supply chains involving electrified freight transportation. There has been and will continue to be, an interest in electrifying freight transportation to minimize the emissions [9]. Studies have been conducted related to electric vehicles and their economic and environmental impact when used as a source of distributed energy storage, that can store and release energy whenever required by the grid [10].

In some cases, balancing of renewables can be achieved with smart charging, also known as delaying charging [11]. In smart charging, the charging of electric vehicles is delayed while not affecting the use of the vehicle, potentially shifting electricity demand to times with more renewables available. Past research has explored the impact of smart charging which can lead to an increase in energy for transportation coming from renewables, and allows for better utilization of renewable energy [12]. As an extension, electric vehicles can be used as a source of energy through a technology known as Vehicle-to-Grid (V2G). In V2G, the charger can discharge the battery of an electric vehicle into the grid by remaining plugged in even after it has finished charging. The impact of V2G technology has been analyzed and, in combination with smart charging, it can enable systems to integrate larger amounts of renewable energy [13]. Various works have shown that V2G and smart charging can: minimize system load, increase renewable utilization, and balance the supply and demand of power [14]–[18]. Most studies focus on charging residential vehicles (e.g. [11]), however, these are only suitable for shifting demand over short timescales (hours) due to consumers' driving demands.

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Typically, supply chain optimization problems aim to meet the demand for goods while minimizing the overall cost of the system. In supply chain optimization, vehicles are routed based on the paths that minimize the distance traveled. Trying to determine the most optimal routes that a fleet should take to deliver goods to customers has led to the development of countless vehicle routing problem models. A review of the vehicle routing problem is explained by [19]. Research has also been conducted on the integration of production scheduling and vehicle routing, and the necessary requirements [20]. A breakdown of a formulation for the vehicle routing problem is shown in [21] which incorporates complexities found in real life and possible ways to solve the problem.

In this paper, we develop a coupled formulation for joint power system and supply chain planning. The power system encompasses the supply and demand of power, which includes both non-renewables and renewables. Supply chain planning involves the distribution of goods to balance the seasonal supply of goods with fluctuations in demand. This differs from past research by presenting a new formulation for the joined power system, integrating the supply chain planning and power system, which usually function independently and are modeled separately. A seven-city case study is explored to demonstrate the effects of our proposed model. Additionally, an economic comparison is made between our proposed model and a battery-operated system.

It is important to note, that the flexibility of the supply chains being leveraged in this formulation comes from the timeline of supply chains, which can span months from the raw material to the delivery of finished goods, and typically in a supply chain most links are not working at full capacity.

II. Problem Formulation

To model the coupling of the supply chain and power system, we develop a formulation that finds the lowest overall system cost. Our problem objective is to minimize the total capital and operation cost of the coupled system, which can be described as:

$$\begin{aligned} \min \quad & \Delta_t N_t \left(\sum_i k_i^{\text{store}} W_i + k^{\text{truck}} Y \right) \\ & + k^{\text{power}} \sum_t z_t + \sum_t \sum_i 10^{-3} p_i^{(t)} \end{aligned} \tag{1}$$

To calculate the total cost of storing goods across time and all locations, the following variables are needed: Δ_t, the size of each time step in hours; N_t, the number of time steps; k_i^{store}, the levelized cost of warehouse storage at a given location i in $\$$/kg-hour, which changes depending on the location being more expensive in a bigger city and cheaper further out; k^{truck}, the levelized cost of each truck in $\$$/hour; W_i, the maximum capacity of the storage facility at location i in kg; and Y, the total number of trucks in the fleet. To determine the use of non-renewables and incentivize efficient energy usage a power penalty, k^{power}, is included in $/KWh, and the number of non-renewables available at each time, z_t, in kWh. Note that in this paper, the power balance model we will be using will be a copper plate model. This means that we are not going to consider the distribution of power and focus on balancing the supply and demand of power. In the objective, we also include the total consumed electricity for each location and time in kWh, $p_i^{(t)}$. In the objective function, 10^{-3} is a weighting factor to create a secondary objective by reducing the effect of the total consumed electricity. This small weighting disincentives solutions that waste renewable power, which could be used by other demand sectors.

The constraints of the coupled optimization problem can be expressed as:

$$\begin{aligned} Y_i^{(t)} = Y_i^{(t-1)} & - \sum_j y_{(i,j)}^{(t)} + \sum_j y_{(j,i)}^{(t-\tau_{ij})} \\ & - \sum_j {y'_{(i,j)}}^{(t)} + \sum_j {y'_{(j,i)}}^{(t-\tau_{ij})} \end{aligned} \tag{2a}$$

$$\begin{aligned} X_i^{(t)} = X_i^{(t-1)} & + s_i^{(t)} \\ & + T_{\text{load}} \left(\sum_j y_{(j,i)}^{(t-\tau_{ij})} - \sum_j y_{(i,j)}^{(t)} \right) \end{aligned} \tag{2b}$$

$$\begin{aligned} C_i^{(t)} = C_i^{(t-1)} + \Delta_t \Bigg(p_i^{(t)} - \sum_j E_{(i,j)} \Bigg(& y_{(i,j)}^{(t)} \\ & - \frac{T_w}{T_w + T_{load}} {y'_{(i,j)}}^{(t)} \Bigg) \Bigg) \end{aligned} \tag{2c}$$

$$\sum_i Y_i^{(t)} + \sum_{ij} \sum_{\tau=0}^{\tau_{ij}} y_{(i,j)}^{(t-\tau)} \leq Y \tag{2d}$$

$$C_i^{(t)} \leq Y_i^{(t)} T_{\text{batt}} \tag{2e}$$

$$\sum_i p_i^{(t)} \leq \sum_i r_i^{(t)} + z^{(t)} \tag{2f}$$

$$X_i^{(t)} \leq W_i \tag{2g}$$

Note that all constraints are for all location i and time t where $t < \tau_{i,j}$.

For simplification, only full trucks and empty trucks are taken into consideration in the formulation to avoid non-linear constraints which would significantly increase computational complexity. To determine the number of stationary trucks in the system at any location and time, constraint (2a) is used. Here, $Y_i^{(t)}$ represents the number of trucks at location i and time t. The term $y_{(i,j)}^{(t)}$ is the number of trucks that leave location i to location j, and ${y'_{(i,j)}}^{(t)}$ are the number of empty trucks that leave location i to location j. The parameter τ_{ij} represents the fixed number of time steps required for trucks to travel from location i to location j. This constraint calculates the number of stationary trucks at location i and time t by considering the number of stationary trucks in the preceding time step, the number of outgoing loaded and empty trucks leaving location i at time t, and the number of incoming loaded and empty trucks.

Constraint (2b) keeps track of the product in the system and how much of it is stored at a specific location and time t. To calculate the amount of product stored at location i at time t, $X_i^{(t)}$, we need to consider the amount of product at the same location in the previous time step, $X_i^{(t-1)}$, and the product injection in kg at location i and time t, $s_i^{(t)}$, where a positive amount indicates an extra supply of the good and a negative amount indicates demand for the good. Moreover, we need to consider the number of products leaving location i at time t by considering the number of full trucks leaving location i to any location j at time t and the total capacity in kg of each truck, T_{load}. Similarly, we need to take into account the total number of full trucks arriving at location i in time t from any location j after a time delay or the time it takes a truck to travel from a specific location j to location i. Through this constraint, the demand of each location is met, satisfying the major goal of a transportation system.

To keep track of the accumulated charge of trucks at each location i we have constraint (2c). In this constraint, the accumulated charge of the current time t, $C_i^{(t)}$ is calculated based on the accumulated charge of the previous time, $C_i^{(t-1)}$, the energy accumulated from grid charging, $p_i^{(t)}$ and the energy lost from the full and empty trucks leaving current location i. To calculate the energy lost we have the amount of energy in kW needed for a full truck to go from location i to location j, $E_{(i,j)}$, by the number of full trucks leaving the current location i to any location j. For empty trucks, we assume that the energy required by the truck changes linearly with the weight of the truck and is thus proportional to the weight ratio of the truck. Thus, the ratio is composed ratio of the weight of a truck T_w in kg over the combined weight of the truck and the carrying load capacity of the truck, T_{load}, in kg. Reminder that Δ_t is the size of each time step in hours.

Furthermore, constraint (2d) ensures that the total number of stationary trucks at location i and time t, Y_i^t, plus the number of trucks traveling in the system must be less than the total number of trucks in the fleet, Y. The total number of stationary trucks at location i and time t is calculated by summing for all the locations the number of trucks at each location i and time t. Meanwhile, the number of trucks traveling in the system is calculated by summing over all the trucks going from location j to location i, taking into account the time delay.

Constraint (2e), makes sure that the accumulative charge at location i for a time t, $C_i^{(t}$, is less than the battery capacity of a truck T_{batt} in kWh multiplied by the number of stationary trucks at location i for time t, $Y_i^{(t)}$.

To ensure that the amount of power being used in kW, $p_i^{(t)}$, is less than the total amount of renewables available, $r_i^{(t)}$ in kW, and non-renewables available in kW, $z^{(t)}$, we have constraint (2f). Note that, since the model is a copper plate, the non-renewable power available is only considered to vary across time, not by location. If we included a complete power network model, we would substitute the following constraint with a set of power flow equations.

The final constraint (2g) ensures that the amount of product at any location i and time t is less than the maximum capacity of the storage facility at location i, W_i.

All the decision variables must be greater than or equal to 0 so we have that:

$$y_{ij}^{(t)}, z_i^{(t)}, X_i^{(t)}, W_i^{(t)}, \hat{Y}, C_i^{(t)} \geq 0 \tag{3}$$

Although the formulation presented uses integer variables for the number of trucks traveling along each path, we relax these variables to be continuous. This allows us to keep the computational burden of the (very large) problem down, although necessitates implementing a rounding policy.

A. BESS Comparison

To see the effectiveness of using the proposed model an alternative model, the battery energy storage system (BESS), and its formulation are presented. In the proposed model, we have a power penalty for non-renewables and trucks acting as mobile batteries to help minimize fluctuations of renewables while still covering demand. Trucks are moved to meet demand and minimize the power penalty for non-renewables.

In our BESS comparison, the decisions for truck schedules are all fixed using the cost minimum solution assuming no penalty is applied to non-renewable power. Then our formulated problem considers whether it is economically viable to install fixed batteries to deal with fluctuations in renewables, motivated by the penalty on non-renewable power. Batteries have a high capital cost but, unlike electric trucks, they do not have an underlying energy demand that must be met. This comparison allows us to benchmark the cost of using supply chain flexibility against stationary energy storage.

To model the BESS we develop an objective that minimizes the total cost of batteries and power penalty for non-renewable energy characterized by:

$$\min \quad k^{\text{batt}} M_{batt} + c^{\text{power}} \sum_t z_t \tag{4}$$

In the BESS model, we assume the electric trucks are charged at a minimum cost, as a result fixing the power demand. To calculate the total cost of the batteries, we take the levelized cost of each battery in \$/kWh, k^{batt}, multiplied by the maximum capacity of the installed battery, M_{batt} in kWh. Additionally, the penalty-cost, k^{power}, for the non-renewable energy being used, z_t, is considered.

The constraints for the BESS model are as follows:

$$B_t = B_{t-1} - p_t + r_t + z_t - r_t^{curt} \quad \forall t \tag{5a}$$

$$B_t \leq M_{batt} \quad \forall t \tag{5b}$$

$$B_0 = B_{N_t} \tag{5c}$$

For constraint (5a), the battery stored energy at a time in kW, B_t, is based on the battery stored energy at the previous time step in kW B_{t-1}, the energy demand at time t, p_t, the renewable energy generation at time t in kW, r_t, the non-renewables used at time t in kW, z_t, and the curtailed energy at time t in kW, r_t^{curt}.

To make sure that the battery energy storage. B_t, is less than the maximum battery capacity, M_{batt} we use constraint (5b).

Finally, to make sure that the battery storage energy at the last period B_{N_t}, where N_t is the number of time steps, equals the battery storage energy at the first period B_0 we have constraint (5c).

All the decision variables must be non-negative leading to:

$$M_{batt}, B_t, r_t^{curt}, z_t \geq 0\,. \tag{6}$$

III. Results

To determine the impact of the formulation, a case study was conducted which included 7 cities in the network: Atlanta, GA; Knoxville, TN; Nashville, TN; Birmingham, AL; Savannah, GA; Chattanooga, GA; and Charlotte, NC. There was a product supply injection in Savannah, GA amounting to 8,000 metric tons that needed to be distributed across the network – with each city in the network having a deterministic time-varying demand for product in kilograms. The case study extended across a 2-month planning horizon and contained hourly time steps. In this case study, we used Gurobi, the optimization solver in Python, which was run on a Dell XPS 16 Laptop.

A. Changes to fleet operation

Figure 1 visualizes the change to the supply chain network when a \$10/MWh penalty on non-renewable power is included. This resulted in an increase of 31.3 MWh of renewable generation utilization when compared to the solution with no penalty on non-renewable power.

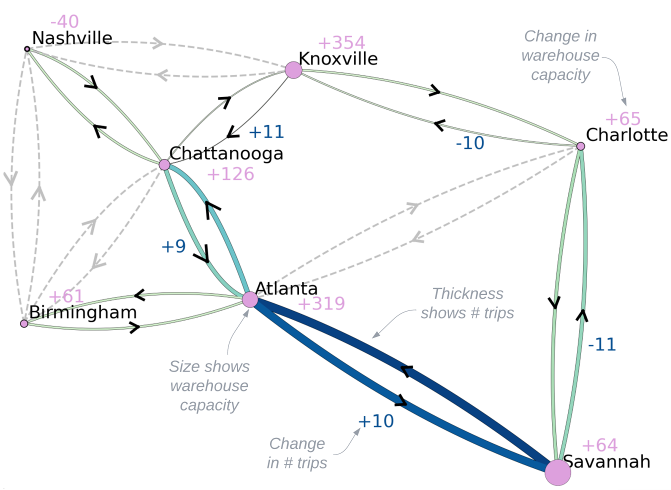

Fig. 1. A visualization of how the movement of goods changed over the two-month simulation with the introduction of a penalty on non-renewable power. It shows the 7 cities of the case study with the line thickness showing the number of trips, the text next to the lines showing the change in the number of trips, the pink circles showing the size of the warehouse capacity, and the text near the circles showing the change in warehouse capacity in kg of product.

The results of the case study showed that the introduction of the power penalty altered supply chain operation, with most cities experiencing increases in warehouse capacity, thereby optimizing the storage of the system. Nashville was an exception containing a slightly decreased warehouse capacity. Specifically, the largest change exhibited was Knoxville with an increase of 354 kg of product in warehouse capacity. The larger warehouse allows the facility to store goods for a longer period, increasing the supply chain's flexibility. The large increase in warehouse capacity is most likely due to the position of Knoxville on the map with its proximity to Nashville motivating the network to store goods in a city with closer proximity to more cities in this case Nashville. Another reason is due to how the demand is distributed across the network. In our model, Knoxville contains a large demand for goods which removes a large quantity of goods from the warehouse in the area.

There was also a decrease in the number of trips between certain cities, with the greatest reduction being between Savannah and Charlotte, at 11 trips. Reduction in the number of trips corresponds to less time on the road for trucks since they will no longer have as many miles to cover, thus reducing emissions and lowering operational costs. Moreover, it allows trucks to spend more time at facilities than the road allowing them more time to act as mobile batteries to deal with fluctuations in power supply from renewables. Conversely, there was an increase in the number of trips between other cities with the largest increase being Knoxville to Chattanooga at 11 trips. Since, the considered case study showed no changes in the total number of trucks in the fleet when using the proposed model, it implies that the increase in a number of trips between some cities is based on the goods taking a slightly different trip from the origin to destination, aligning it better with the generation of renewables.

B. Comparison with battery energy storage

To assess the economic effectiveness of the proposed model, a comparison was conducted between utilizing supply chain flexibility and BESS. As mentioned before, the proposed model takes into consideration a power penalty for non-renewable energy and utilizes electric freight to motivate the use of renewables. Meanwhile, in BESS, batteries are implemented in the system if it is economical to provide balancing services to the power system and increase the utilization of renewables.

To check the effect that changing the incentive for renewable energy in \$/MWh had on the proposed model and the BESS model, we examined how the amount of renewables used in MWh changes as the incentive increases. For the proposed model, as the incentive grew, the amount of renewable energy used increased. For the incentives of 0.01, 0.1, 1, 10, and 100 \$/MWh, the increase in renewable energy used across the two-month horizon was 27.6, 28.5, 31.3, 37.1, and 99.8 MWh, respectively. Meanwhile, when the incentive was smaller at 0.01 and 0.1 \$/MWh, BESS did not use any renewable energy, most likely due to the high cost of batteries. However, as the incentive grew, BESS began to use up more renewable energy with at the incentive of 1, 10, and 100 \$/MWh, the renewable energy used was 31.3, 108.6, and 134.8 MWh respectively. The comparison can be seen in Table I.

These results demonstrate that for an incentive lower than 1 $/MWh our proposed model increases the use of renewable energy compared to the BESS model and thus is better at integrating renewables with little incentive. The BESS model does not shift towards renewables until the incentive is larger than 1 $/MWh, meaning it needs a larger incentive to outweigh the batteries' cost. BESS requires batteries to deal with the functions of the power supply. Since the objective of the model is to minimize cost, the BESS model does not find it economical to utilize renewables until it has an incentive high enough to balance the cost of the batteries and make integrating batteries into the system worthwhile. Once the incentive is large enough to add batteries, the renewable energy used increases more rapidly for BESS than for the proposed model. Considering that once a battery is put into place and we have the initial capital investment it can allow renewable energy to be used at no additional cost until further batteries are needed, in other words, until the capacity of the batteries is met. However, this will lead to significant expenses due to the cost of the batteries when we want to integrate higher amounts of renewables into the system for longer. Thus, the proposed method is better for allowing the system to use renewable energy more effectively with fewer incentives and more consistently.

Incentive ($/MWh)	**Additional Renewables Used (MWh)**	
	Proposed	**BESS**
0.01	27.6	0
0.1	28.5	0
1	31.3	31.3
10	37.1	108.6
100	99.8	134.8

TABLE I
RENEWABLE ENERGY CONSUMPTION FOR VARIOUS PRICE INCENTIVES, COMPARING THE FREIGHT RE-DISPATCH METHOD WITH BATTERIES.

IV. CONCLUSION

In this paper, we analyzed whether flexibility in electric freight dispatch can be leveraged to offset fluctuations in renewable energy generation. A problem formulation was constructed containing components from the power system and supply chain planning to create a coupled system that minimizes the total cost of the system. A case study was carried out to evaluate the effectiveness of the coupled system formulation, comparing the proposed model with the battery energy storage system. The case study demonstrated how the proposed system benefited the network by altering the warehouse capacity and modifying the number of trips taken increasing the renewable generation utilization of the system. Meanwhile, the comparison showed that the proposed model was effective at using more renewables with lower incentives in ($/MWh) than the battery energy storage system due to not having large initial capital investments. Further research should focus on a larger more realistic case study to analyze the proposed model for a real-world problem.

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