Cost-Reducing Optimization Strategies of Electrical Trains

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Abstract— **The development of Railway Smart Grids (RSGs) has multi-fold benefits [1]. Trains are flexible demands and thus it is possible to have a multitude of velocity profiles satisfying the same end-to-end time constraints. This opens up the opportunities of cost of energy optimization in RSGs in addition to energy optimization in electric railways. In this paper, we have proposed the idea of transaction of energy between the trains and external loads when there is a difference between the day-ahead and real-time electricity price. This is made possible by the flexibility of the power demand of the trains. This case has been analyzed on Acela express running on Northeast Corridor for different trips. The results show promise in that the participating entities can make profit on successful price negotiation.**

Keywords—Electric Train, Cost, Energy, Optimization

I. INTRODUCTION

Energy management in electric railway systems is a huge challenge, considering the number and type of players involved in it – trains, electric grid, way-side energy storage systems etc. The development of smart railway grids which involve pervasive sensing and coordinated information exchange between various participants in real time, yields distributed control and thus creates an exciting opportunity of integrating the scheduling of the train to the economy of its operation.

Different approaches have been made towards optimizing the energy consumption of electric railway systems. Time-table optimization and driving strategy optimization are two different optimization approaches adopted for railway energy minimization. To meet the variable passenger demand, the railway operators schedule several timetables in advance and choose one based on passenger flow., Many formulations have been proposed for cyclic timetable formulation for minimizing passenger waiting times and delay times, headway-control, etc. [2]-[4]. On the other hand, many studies have focused on efficient driving strategies for minimizing the energy consumption between stations. The works [5]-[7] analyzed the Pontryagin's maximum principle for minimum energy consumption for various track conditions and trip durations and obtained the optimal operating modes of the trains. Khmelnitsky [8] considered the problem of energy minimization in a track with variable gradients and speed limit sections. He also showed that if regenerative energy can be fully recovered during the braking phase, the coasting phase will be interrupted in the optimal speed profile. Studies have also been performed on adjusting the speed profile of the trains according to the braking time of other trains in a multi-train system to effectively utilize the recovered regenerative energy [9], [10]. Another aspect has been the application of evolutionary algorithms to solve the optimal switching strategy [11]. They have an advantage over the numerical methods when it comes to solving complex systems, but their accuracy and speed are limited when it comes to solving real-time systems.

But, the minimization of energy utilization does not necessarily imply the minimization of the cost for energy utilization of the Railway Power System (RPS). It implies that at any given instant, even if the operation of an electric train is not so set such that it minimizes the overall energy consumption, spread over the entire network of trains, the overall operational cost for energy utilization is minimized. This is a unique opportunity that can be exploited not only for existing and planned high-speed inter-state and inter-city electric trains but for existing and planned intra-city electric trains potentially as well, where the frequency of travel is higher even though the distance of travel is smaller [13]. For the same end-to-end scheduling time of a train, corresponding to a given average velocity of the train, there may exist a plurality of instantaneous velocity profiles one of which may yield the lowest cost of electricity usage. This is shown in Figure 1.

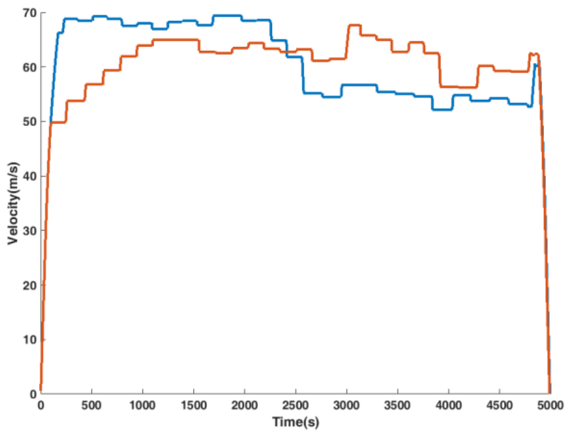


Figure 1. Multiple velocity profiles with same trip time

This flexibility is the key to achieving different objectives which also lead to the possibility of the RPS behaving as transactive nodes. In this paper, the concept of transaction of energy applied to the electric trains utilizes the demand-shifting capability of the trains, where the participating entities can make profit depending on where and when it is applied.

Section II provides the approach for energy transaction for RPS used in this paper. Section III describes the different optimization objectives and how the energy transaction has been formulated, and Section IV presents the simulation analysis succeeded by Sections V which concludes the work.

II. Transactive Control Approach

Figure 2 below shows a broad classification of driving strategy optimization approaches that exist for electric and diesel trains. Electric trains provide a unique mechanism for saving part of its transient energy by feeding it back to the railway grid using regenerative action when it decelerates or comes to a stop at a station. This means that an electric train can behave both like a demand as well as a generating source.

This also leads to the possibility of scenario-centric transaction control opportunities. When there is an external load controlled by the Load Serving Entity (LSE) that has an emergency power demand that is to be met, RPS can act as a transactive agent, willing to send a virtual power by reducing its contracted energy consumption during a stipulated time interval so that the grid can feed this energy to the external load. When the train's trip is expected to end during the same price-hour, it can run an optimization check and determine whether it will be able to meet the schedule economically while still making profit.

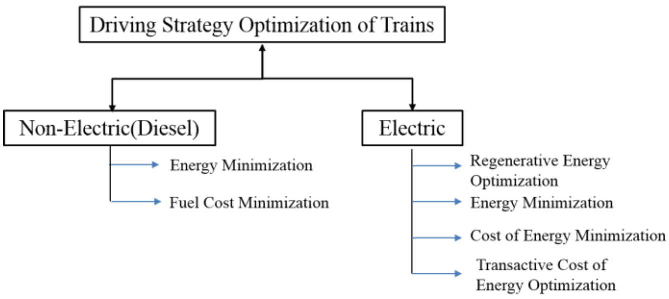


Figure 2. Driving strategy optimization approached for electric and diesel trains

The transactions evolve over different temporal scales ranging from day-ahead online transaction between the power grid and the railway system operators yielding price optimality to real-time optimal transaction among the trains (T) or the area control centers (ACC). The possible opportunities for transaction within the Independent System Operator (ISO)-RPS-LSE is shown in Figure 3.

All of these transactions are carried out while meeting system constraints ranging from end-to-end time-scheduling, power-quality, and capacity.

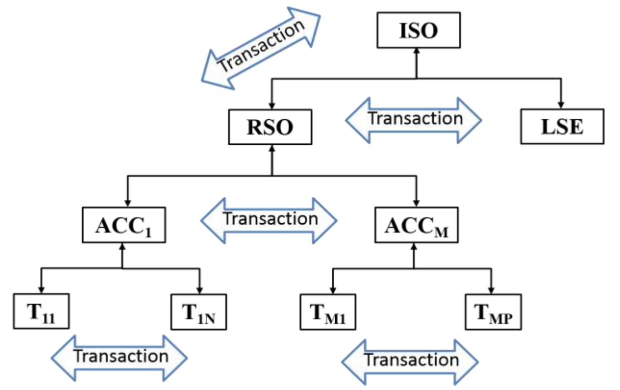


Figure 3. Possible transaction opportunities within ISO-RPS-LSE.

III. Electric Train Model

A. Assumptions

- The mass of the train is assumed constant throughout the simulation and is multiplied by a factor of 1.1 to consider the rotational effect.
- The traction force and the braking force depend on velocity and they can be varied continuously.
- With regenerative braking capabilities, the energy conversion efficiencies are assumed to be 70%.

B. Model

Figure 4 shows the forces acting on a single train, governed by the Newton's law as shown below:

$$M.a = F_{tr}(v) - F_r(v) - F_c(s) - F_g(s) \qquad (1)$$

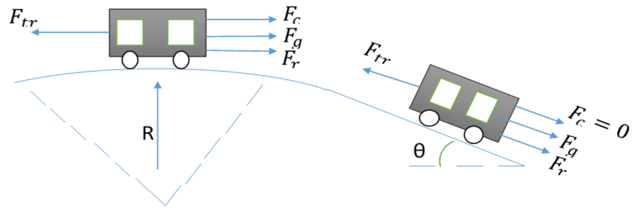


Figure 4. Forces acting on a train travelling through a slope and curve

where, M is the total mass of the train including rotational effect (kg), a is the acceleration/deceleration of the train (m/s^2), $F_{tr}(v)$ is the traction/braking force of the train (N), $F_r(v)$ is the air drag and rolling resistance combined (N), $F_c(s)$ is the resistance due to curvature (N), $F_g(s)$ is the gradient resistance force (N). The F_{tr} is determined by the driver by moving the throttle in one or the other direction, according to a journey booklet which specifies the timetable for reaching several points and the objective speeds to be followed in every point. The objective of this optimization is to determine the content of this journey booklet, in such a way that the velocity profile is the optimal driving strategy for a specific optimization objective.

The formulae for $F_r(v)$, $F_c(s)$ and $F_g(s)$are given below:

$$F_g(s) = M * g * \delta(s) \qquad (2)$$

$$F_r(v) = A + B.v + C.v^2 \qquad (3)$$

$$F_c(s) = \begin{cases} M * g * \frac{D}{1000*R(s)}, R(s) > 10 \\ 0, \qquad otherwise \end{cases} \qquad (4)$$

where $A, B, C,$ and D are empirical constants, $R(s)$ is the radius of curvature at position s and g is the acceleration due to gravity. The power consumed by the train is then calculated as follows:

$$P_{train} = \frac{F_{tr}.v}{\eta} + P_{ancillary} \qquad (5)$$

where, the symbol η is the energy conversion coefficient from electrical to mechanical, $P_{ancillary}$ is the power consumption of the ancillary equipment (heating/air conditioning, cooling equipment, lighting, etc.).

The energy consumption of a journey E_{train} can be calculated as shown:

$$E_{train} = \sum_{t=t0}^{T} P_{train} \quad (6)$$

C. Optimization

The different optimization approaches and comparison of their formulation are detailed in this section. The operation of the train is constrained by the speed limits of the track and the train, acceleration and deceleration limits of the train and the terminal constraints. The speed limits on the track, v_{max}, are imposed due to the track conditions such as gradients, curves or tunnels. The limits on acceleration and deceleration rates of the train, a_{max}, and a_{min} are imposed also keeping in mind the passengers' comfort. Also, there is an operation limit on the maximum traction and the maximum braking force depending on the velocity of the train, $F_{max}(v)$. T_{min} and T_{max} are the minimum and maximum allowed time limits for reaching the station and T is the trip time. The minimum and maximum limit of the trip time is obtained from the schedule and the train operator is penalized for violating the same.

more economical for the Railway System Operators (RSO). The day-ahead cost of electricity that has spatial and temporal variations $\lambda(t,s)$ is multiplied by the instantaneous power $P(t,s)$ to obtain the cost of energy utilization for the trip. Thus, the objective function and constraints for this case are shown in column 2 of Table 1.

In the scenario where the real-time (RT) electricity price is higher than the day-ahead (DA) price, consider an external load L which has a sudden requirement of power for a small duration. The load L requests power from the adjacent TNs where the RSG is one of them. Then the sequence of events follows as far as the train/RSO is concerned.

1. The train runs a schedule check to determine if it can meet up with its original schedule within the allowed delay time.
2. If yes for (1), then it runs an economic viability check to determine whether it will still be able to make profit if it adjusts its energy consumption in real-time.
3. If yes for (2), then the external load L and the train (RSO) negotiate the price that is to be paid by the load L to the train so that both the parties win.

Table 1. Comparison of optimization objectives.

	Case 1. Energy Minimization	Case 2. Cost of Energy Minimization	Case 3. Transaction with External load
Objective function	Min $\Sigma_{s=0}^{S} \Sigma_{t=0}^{T} P(t,s)$	Min $\Sigma_{s=0}^{S} \Sigma_{t=0}^{T} \lambda(t,s) * P(t,s)$	Min $\Sigma_{s=0}^{S} (\Sigma_{t=0}^{t'} \lambda(t,s) * P(t,s)$ $+(\Sigma_{t=t'}^{T} \lambda'(t,s) * P'(t,s))$
Constraints	$v \leq v_{max}$ $F_{tr}(v) \leq F_{max}(v)$ $T_{min} \leq T \leq T_{max}$ $a_{min} \leq a \leq a_{max}$ $v(s=0)=0,\ v(s=Station)=0$	$v \leq v_{max}$ $F_{tr}(v) \leq F_{max}(v)$ $T_{min} \leq T \leq T_{max}$ $a_{min} \leq a \leq a_{max}$ $v(s=0)=0, v(s=Station)=0$	$v \leq v_{max}$ $F_{tr}(v) \leq F_{max}(v)$ $T_{min} \leq T \leq T_{max}$ $a_{min} \leq a \leq a_{max}$ $v(s=0)=0,\ v(s=Station)=0$ $E_{[t':t'+\delta t]}^{act} \leq E_{[t':t'+\delta t]}^{orig} - E_{[t':t'+\delta t]}^{request}$

Comparison of different cases of optimization approach-objective functions and constraints are shown in Table 1. For an electric train with regeneration, the objective is to minimize the total energy consumed, also considering the regenerative energy maximization. The instantaneous power $P(t,s)$ has to be summed up over the entire trip for obtaining the total energy of the trip. Thus, the objective function and constraints for this case are shown in column 1 of Table 1.

The electricity prices, in general, have spatial and temporal variations. In such a case, the energy minimization may not lead to a minimum cost of energy utilization. Hence for a train that passes through zones with spatial and temporal price variations, minimizing the cost of energy utilized will prove

The external load requests $E_{[t':t'+\delta t]}^{request}$ MWh of energy for δt duration starting from time t'. The optimizer determines the feasibility and profitability of the RPS by evaluating the following optimization problem: The actual energy consumption of the train $E_{[t':t'+\delta t]}^{act}$ has to be less than the original contracted energy consumption $E_{[t':t'+\delta t]}^{orig}$ during the requested time by the requested amount of energy $E_{[t':t'+\delta t]}^{request}$. Here, $P'(t,s)$ is the adjusted instantaneous power consumption of the train and $\lambda'(t,s)$ is the new price vector. The RSO has to pay the RT price for the excess energy consumption greater than the contracted amount and will have to pay DA price otherwise.

IV. Simulation

The Acela express running from Boston, MA to New Haven, CT has been considered for the simulation. Differential Evolution [12] solver has been used for optimizing the velocity profile to achieve different objectives. The curve resistance has not been considered. The maximum and minimum deceleration limits are taken as 1.23 m/s^2 and the maximum speed of Acela is 217 miles/hr. The maximum traction force curve is shown in Figure 5.

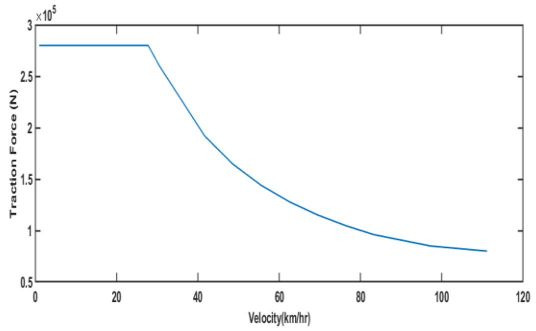


Figure 5. Maximum traction force curve

Acela's first leg of journey between Boston, MA and New Haven, CT is fed from a 60 Hz, 25 kV overhead catenary system whereas the trip from New York City to Washington DC is supplied by a 25 Hz 12 kV catenary system. The ISO-NE is the wholesale energy provider in the regions of Boston, Rhode Island and Connecticut and NYISO feeds the New York region and PJM is the ISO operator for the New Jersey to Washington D.C.

For the trip of Acela that has been considered for this in our simulation, the trains pass through 4 zones where the electricity prices vary with time. The zones that are considered are NE Mass. (4008), SE Mass. (4006), Rhode Island (4005), and Connecticut (4004).

The zonal day-ahead electricity pricing information has been obtained from [14] for June 27, 2019. The hourly price variation between the zones of Richmond (RI) and Connecticut (CT) are shown in Figure 6 and the results of energy and cost of energy optimization are compared in Table 2. It can be observed that there is a huge price variation between the zones during the hours 15-20 and hence the trains that pass through these zones during these periods can make profit by performing cost of energy optimization. The price variation makes the optimizer choose the profile such that the energy consumed during the high-price hours is minimized. The results are compared in Figures 7 (a) and (b).

The schedule of the trains also determines the cost of energy utilization. As it is evident from the Figure 6, the electricity price variation between the two zones is not much during the hours before 3 pm and after 8 pm. Both of the optimization objectives would yield similar results when the price difference is not much.

From the velocity profile, it can be verified that the trip time for the journey remains the same, whereas the brown curve achieves the minimum cost of energy operation.

Table 2: Comparison of Energy and Cost Minimization Objectives

	Minimization of Energy Objective	Minimization of Cost Objective
Cost of Energy ($)	73.9883	71.6609
Energy (kWh)	1573.4	1601.3

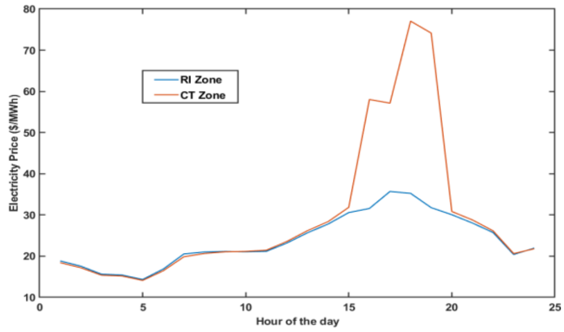
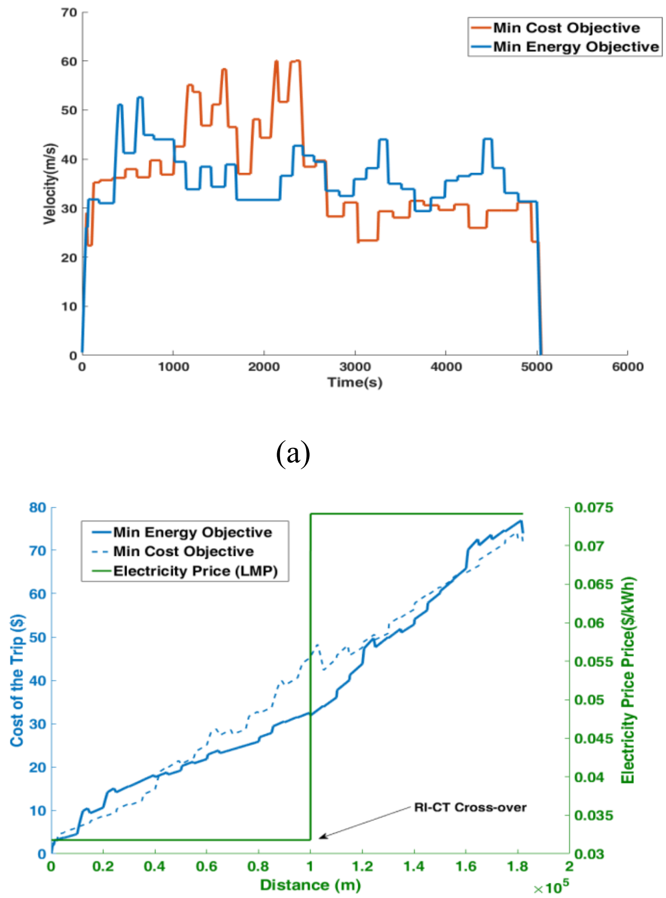


Figure 6. Day ahead hourly price variation for RI and CT zone on June 27, 2019.



(a)

(b)

Figure 7. Comparison of (a) velocity and (b) Cost of Energy profile between minimization of energy and minimization of cost of energy objectives.

The Figure 7 (b) shows the cost of the trip against the trip duration. It can be observed that the Min Cost profile consumes more energy during lower price periods i.e., before the RI-CT crossover so that it finishes the trip with lower cost of energy utilization than the minimization of energy case. There is a reduction in cost of energy utilization by 3.14% for an increase in energy utilization of only 1.77%.

In order to assess the profit of cost optimization for a single day, cost of energy utilization for the trip between Providence, RI to New Haven, CT, for a weekday is found out. The price difference between the contiguous zones could be anywhere between -0.01 $/MWh and 112 $/MWh based on our analysis. The RT hourly electricity price for February 4, 2016 is considered in our simulation which exhibits greater price variations as shown in Figure 8.

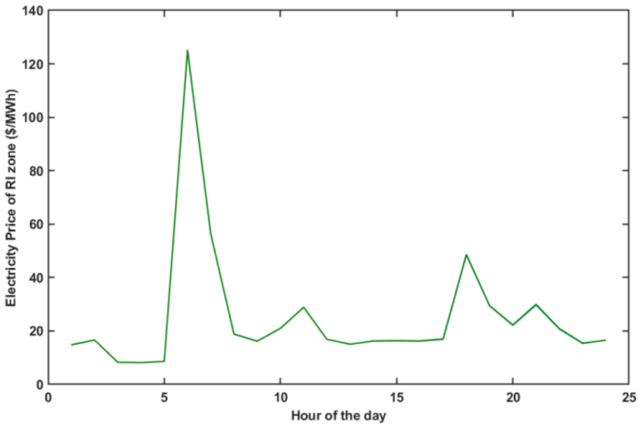


Figure 8. Electricity price variation in RI zone on Feb 4, 2016.

The total cost for all the trips from Providence, RI to New Haven, CT on Feb 4, 2016 is tabulated in Table 3.

Table 3. Comparison of daily cost for Providence, RI to New Haven, CT trips for a single day.

	Minimization of Energy Objective	Minimization of Cost Objective
Daily Cost for Providence-New Haven Trip ($)	409.4751	349.9803

From the results, the weighted cost minimization has a profit of 14.53% over the energy minimization for all the trips from Providence, RI to New Haven, CT, for a single day.

This comparison is valid only for the particular trip for a particular electricity price-day since the electricity prices vary widely over time and space. This implies that the schedule of the train, its trip time, and the pricing zones through which it passes also affect the variation in cost of energy. To address the possible variations and to see the profitability with cost of energy minimization, the factors of zonal price variations, distance and speed are varied and are tabulated in Table 4. Here, Trip A is taken as the base case and Trip B has the same distance as A, but with maximum speed = 60% of maximum speed of Trip A. Trip C has the same maximum speed as Trip A, but its distance = 60% of distance of Trip A. It is assumed that there are only two price zones for all the trips. Factor on the first column of Table 4 is the ratio by which the electricity prices of the two pricing zones vary.

Table 4: Comparison of profit with cost optimization when considering energy optimization as the base case for the trips A, B and C.

	Trip A	Trip B	Trip C
Factor =1.5	3.5%	0.49%	1.69%
Factor =2	7.3%	0.82%	4.6%
Factor =5	21%	1.37%	11.1%

This shows the profitability of the approach when considering millions of dollars spent in electricity consumption for the whole year. From this it is clear that the benefits with cost minimization will be more pronounced when considering:

1) Longer trips with higher speeds.
2) Greater price variations between the adjacent zones.
3) Schedule of the trips and trips during peak period.

The results are indicative of a proof that aiming for cost of energy utilization will lead to lesser cost of energy utilization when employed for all the trips of its journey. This shows that the cost of energy minimization will prove more profitable in the long run, when the US is expected to have a larger network of higher speed trains.

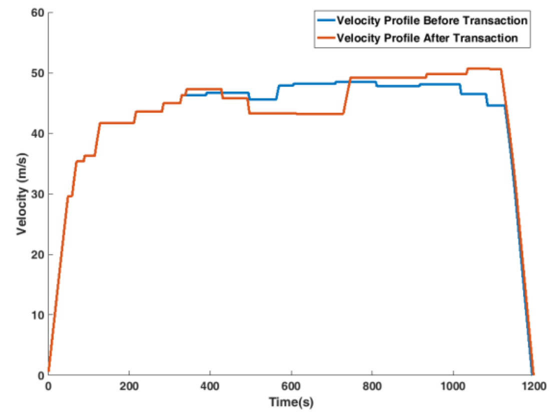
A. *Transaction of Energy with an External Load*

The DA and RT prices for Feb 13 for the two zones of NE Mass. and SE Mass. of ISO-NE are shown in Table 5.

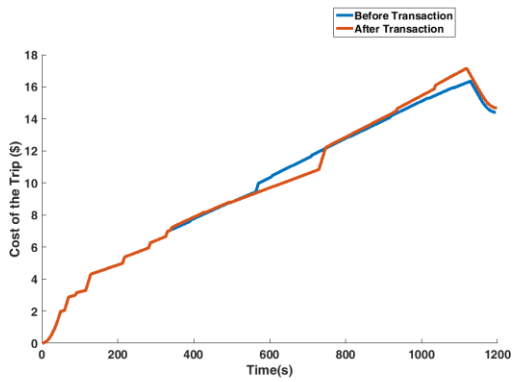
Table 5. DA and RT prices for the 2 zones NE Mass. and SE Mass. of ISO-NE.

	DA-price ($/MWh)	RT- price ($/MWh)
Zone 1	24.14	35.22
Zone 2	24.05	34.99

The train contracted the energy requirement for the trip day-ahead. The external load requests an average power of 0.5 MW from the train for 5 minutes which is equivalently, 0.5/12 MWh. The train relinquishes the equivalent amount of energy from 400 to 700 sec. But the train receives this request at 300 s and starts adjusting its consumption from 340 s, if it is economically feasible. Price to be paid by the load to the grid with RT price of $35.22/MWh= 35.22*1*(0.5/12) = $1.4675. The train determines that if it relinquishes the amount of energy requested, it will have to incur an excess of only $0.4 from the initial cost of energy of $14.4284, with no delay in reaching its destination. The RSO can enter into negotiation with the external load and determine a price that would be profitable to both entities. The reduction in cost of energy for the RSO can be anywhere between 0-9.89 % based on the negotiation. The velocity profiles corresponding to both cases is shown in Figures 9 (a), (b) and (c).



(a)



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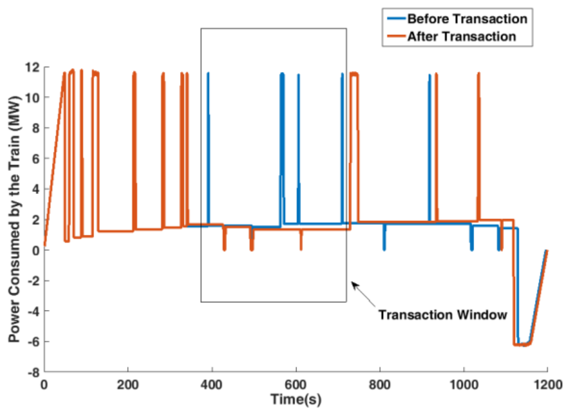

(c)

Figure 9. Comparison of (a) velocity (b) cost of energy and (c) power profiles before and after energy transaction

The RSO determines that the train can alter its consumption when travelling through a low-price-hour area and still make additional money through exchange of demand with the external load. Figure 10 below shows the maximum reduction in electricity cost for the RSO when transacting with the external load, when the RT prices of the zones are higher than the DA contracted price by an average of 43%.

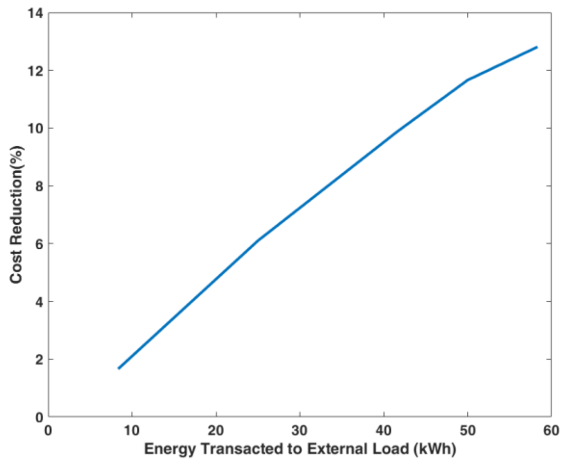

Figure 10. Cost Reduction (%) of the RSO while Transacting with the External Load without Violating the Scheduling Constraints.

This is the maximum cost reduction (%) plotted against the energy transacted to the external load (kWh). The train would not be able to achieve a reduction in its cost without violating the scheduling constraints if it were to transact more than 60kWh during this trip of 51.5.This is economically viable when the train travels through different areas with different real-time prices. It is this flexibility of power consumption that enables the energy transaction, leading to further reduction in cost.

V. Conclusion

In this work, application of weighted cost minimization and energy transaction has been explained as methods to reduce the cost of energy utilization of electric trains. The benefit of cost reduction with the cost-optimal profile are shown for various cases. The opportunity for energy transactions between the train and an external load or between trains could also be beneficial during times when the grid is highly stressed. The variations in the external factors such as the number of passengers, weather conditions, unexpected delays, comfort constraint variations, geographic variations of electricity price and storage elements are expected to have an effect on the transactions.

Acknowledgment

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