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Illegitimate Trade Detection for Electricity Energy Markets

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Abstract—**This paper proposes a novel algorithm for detecting trade activities suspected to be illegitimate across day-ahead and real-time energy markets. Illegitimate trades bring severe risks to the financial health of energy markets and the operation stability of power grids. It is of critical importance for the operators to identify such activities in a sound and timely manner. The proposed algorithm firstly generates a set of legitimate trade feature samples using historical trade profiles of energy markets based on the comparison of day-ahead and real-time trade profiles and related environmental impacts. Then a set of illegitimate trade feature samples are created using a Genetic-algorithms based negative selection procedure based on those legitimate trade feature samples. The created illegitimate samples are further labeled with specific illegitimate trade types by comparing with pre-defined typical trade feature samples for each illegitimate trade type. After that, deep learning is employed to learn the relationship between the trade features and associated legitimacy labels from the sets of legitimate and illegitimate trade feature samples, and predict the legitimacy status for incoming trade profiles according to corresponding trade features. The effectiveness of the proposed algorithm has been demonstrated using sample trade profiles obtained from New England ISO.**

Keywords— anomaly detection, electricity energy markets, genetic algorithms, illegitimate trade, negative selection

I. Introduction

Deregulated energy markets were created to harness the powers of competition in promoting efficient markets and competitive prices for energy consumers. The design and operation of these markets is complex and susceptible to participant conduct that can threaten their efficiency and integrity [1]. Market operators are responsible for protecting the efficiency and integrity of the markets by monitoring, investigating and enforcing compliance with the various rules prohibiting such conduct. The types of such conduct generally can be divided into two basic categories, market power and market manipulation.

There are many works existing on identification and mitigation of market powers [2]-[5], but insufficient efforts on detection of market manipulation [6]. In light of this, this paper has focused on the detection of illegitimate trading, i.e. market manipulative behaviors across day-ahead and real-time energy markets. The detection is based on the comparison of scheduled day-ahead trading profiles with executed rea-time trading profiles and considering the impacts of weather and other environmental factors.

The energy trading activities between day-ahead and real-time markets may be deviated to some extent, but inherent energy usage patterns should be closely matched each other to avoid significant operation cost increase in power grid, and unfair economy benefits to market participants.

The electricity energy markets collect a large amount of data from market participants at different time scales, but are lack of legitimacy information about those trading activities. Illegitimate trade can be defined as a pattern in the trade activities that does not conform to the expected legitimate trading behaviour. Generally speaking, illegitimate trading events occur relatively infrequently. However, when they do occur, their consequences can be quite dramatic and quite often in a negative sense.

In this paper, a novel detection method is proposed to detect the illegitimate trading activities across day-ahead energy market and real-time energy market. The used data for trade legitimacy identification include the cleared energy bids for each day-ahead bidding intervals, and the executed energy bids for each real-time bidding intervals for a given trader, or a group of traders. The deep learning approach is used to label the given trading activities as legitimate, or illegitimate with specific types based on a set of feature attributes. The illegitimate trading can be classified into different types, such as peak hour manipulation, valley hour manipulation, and others. Each trade set is evaluated using multiple feature attributes, including peak shortage, valley excess, capacity fitting, up-ramp shortage, down-ramp shortage, ramping fitting, correlation between markets, and environmental impact by comparing the cleared day-ahead data, and real-time usage data, and evaluating the environmental conditions.

Considering that there are rarely labelled illegitimate data available, and the boundary between legitimate and illegitimate behaviour is often not precise due to legitimate behaviour keeping evolving with time, the proposed algorithm solely depends on historical legitimate trading sets to build illegitimate detection model. For each data set of legitimate trading, we have determining a set of feature attributes to represent its legitimate status. Then, using a Genetic-algorithms based negative selection approach, a set of illegitimate trade feature samples are generated based on the determined set of legitimate trade features. The generated illegitimate trade feature samples are further assigned a specific label for different illegitimate status by comparing with pre-defined typical trade feature samples for each illegitimate trade type. The typical illegitimate trade feature samples can be determined based on corresponding set of day-ahead and real-time trading profiles generated by simulating a specific illegitimate trade type. The legitimate trade feature sets and labeled illegitimate trade feature sets constitute the training data sets for the deep learning model.

The proposed algorithm treats the illegitimate trade detection as a multi-class classification problem and modeled through a forward neural network with multiple hidden layers.

The inputs and outputs are set as feature attributes and legitimate status of samples. For a new trade set, based on the corresponding feature attributes for the new sample, then the legitimate status for the given trade can be determined accordingly.

The proposed algorithm has been tested using historical trade profiles for a load zone at Northeast Massachusetts and Boston area and historical weather observations at Boston weather station. The original trade profile are obtained from New England ISO, and modified to represent illegitimate trade scenarios for facilitating algorithm testing. The trade profiles are represented as cleared day-ahead hourly demands, and executed real time 5-minute demands. The weather information includes hourly dry-bulb and dewpoint temperature observations. The trade activities and weather conditions for three months of 2019 are used, in which the data sets of July and August of 2019 are used to train the illegitimate trade detection model, and the ones in September of 2019 are used for testing the performance of the model. We have modeled four different illegitimate trade behaviors, including peak hour manipulation, valley hour manipulation, up-ramping period manipulation, and down-ramping period manipulation. The test results on the sample trade profiles have showed that the proposed algorithm can correctly identify the legitimacy of trade activities, and assign corresponding legitimacy label with accuracies of 95.50% and 94.63%, respectively.

II. Characteristic Measures for Illegitimate Trades

We define eight different measures to characterize the features of trade profiles for identifying illegitimate trades, in which 7 of them are determined based on the comparison of cleared day-ahead bids and executed real-time bids or real-time bids to be executed, and the other is used to represent environmental impacts for preventing misplacing environment-induced demand deviations as manipulative behaviors. For each trade set, we can correspondingly determine a set of features. Based on those features, we can determine whether the trade activity is legitimate or not, and if it is illegitimate, what type of illegitimate it belongs to.

It is noted that the formulas for trade feature calculation might be slight difference between ones for a power producer and for a power consumer. The bided powers used in the formulas refer to the purchased or purchasing amount of powers for a power consumer, and the sold or selling amount of powers for a power producer. The formulas are given for any trader or trader group in the markets. The trader can be a single power producer, or a group of power producer such as virtual power plants (VPPs). The trader can also be a single power consumer, or a group of power consumers, such as load serving entities (LSEs).

Assumed that each day-ahead time interval includes N_s real-time time intervals, each day-ahead cycle includes N_h day-ahead time intervals, and the monitoring window used by the operators includes W day-ahead time intervals. The average actual real-time energy bid for a given day-ahead time interval h, $\hat{P}_h^{RT}$ can be determined as:

$$\hat{P}_h^{RT} = \frac{1}{N_s} \sum_{m \in M(h)} P_m^{RT} \quad (1)$$

where P_m^{RT} is the actual real-time bid for a real-time interval m, $M(h)$ is the set of real-time intervals within the given day-ahead interval h. For each day-ahead time interval h within the monitoring window, the average real-time energy bid $\hat{P}_h^{RT}$ is compared with the cleared day-ahead energy bid P_h^{DA} to evaluate the impacts of power deviations across different markets on the system capacity and response speed requirements. The monitoring window includes W day-ahead intervals retrieved from the study day-ahead interval.

The first characteristic measure is a peak shortage attribute, $A_h^{peak-short}$ which is used to measure the power mismatch between average actual real-time bid and cleared day-ahead bid during a peak period over the monitoring window. The peak shortage attribute is normalized with the maximum day-ahead bid over the past day-ahead cycle. The peak shortage attribute for a given day-ahead interval h, $A_h^{peak-short}$ is defined as the ratio of the accumulated power deviation $\Delta P_{h-h'}^{RT-DA}$ for all common day-ahead intervals between the peak period and the monitoring window, over maximal day-ahead bid among the past day-ahead cycle, $\overline{P}_h^{DA}$:

$$A_h^{peak-short} = \frac{\sum_{h'=\mathbf{0}}^{W-1} \left[0.5+0.5sgn(P_{h-h'}^{DA} - \alpha^{peak}\hat{P}_h^{DA})\right] \max\left(\mathbf{0}, \Delta P_{h-h'}^{RT-DA}\right)}{\overline{P}_h^{DA}} \quad (2)$$

where $sgn(\cdot)$ is a sign function, $[0.5 + 0.5sgn(x)]$ equals 1 and not 0 only when x is greater than 0. α^{peak} is a peak scale factor which is greater than 1.0. $\hat{P}_h^{DA}$ and $\overline{P}_h^{DA}$ are the average and maximal day-ahead bids within the past day-ahead cycle retrieved from the study interval h, and defined as:

$$\hat{P}_h^{DA} = \frac{1}{N_h} \sum_{h'=\mathbf{0}}^{N_h-1} P_{h-h'}^{DA} \quad (3)$$

$$\overline{P}_h^{DA} = \max_{h'=\{\mathbf{0},\mathbf{1},\cdots,N_h-\mathbf{1}\}} P_{h-h'}^{DA} \quad (4)$$

$\Delta P_{h-h'}^{RT-DA}$ is the power deviation defined as the difference between cleared day-ahead bid and average real-time bid for a power producer as shown (5a), or the difference between average real-time bid and cleared day-ahead bid for a power consumer as shown in (5b):

$$\Delta P_{h-h'}^{RT-DA} = P_{h-h'}^{DA} - \hat{P}_{h-h'}^{RT} \quad (5a)$$

$$\Delta P_{h-h'}^{RT-DA} = \hat{P}_{h-h'}^{RT} - P_{h-h'}^{DA} \quad (5b)$$

The peak period for the study day-ahead interval h is defined as the set of day-ahead time intervals that the cleared day-ahead bid is greater than the average day-ahead bid, $\hat{P}_h^{DA}$ times the peak scale factor α^{peak}.

The second characteristic measure is a valley excess attribute, $A_h^{valley\_excess}$ which is used to measure the difference between cleared day-ahead and average actual real-time bid during valley period over the monitoring window. The valley excess attribute is normalized with the maximum day-ahead bid over past day-ahead cycle. The valley excess attribute for a given day-ahead interval, $A_h^{valley-excess}$ is defined as the ratio of the accumulated power deviations between day-ahead and real-time, $(-\Delta P_{h-h'}^{RT-DA})$ for all common day-ahead intervals between the valley period and the monitoring window, over maximal day-ahead bid within the past day-ahead cycle:

$$A_h^{valley-excess} = \frac{\sum_{h'=\mathbf{0}}^{\mathrm{W}-1} \left[0.5+0.5sgn(\hat{P}_h^{DA}/\alpha^{valley} - P_{h-h'}^{DA})\right] \max\left(\mathbf{0}, -\Delta P_{h-h'}^{RT-DA}\right)}{\overline{P}_h^{DA}} \quad (6)$$

The valley period for the study day-ahead interval h is defined as the set of day-ahead time intervals that the cleared day-ahead bid is less than the average day-ahead bid, $\hat{P}_h^{DA}$ divided by a valley scale factor α^{valley}. The valley scale factor is greater than 1.0.

The third characteristic measure is a capacity matching attribute, $A_h^{\mathrm{capacity\_matching}}$ which is used to measure the capacity difference between cleared day-ahead and average actual real-time bid over past day-ahead cycle. The capacity matching attribute is normalized with the maximum cleared day-ahead bid over the past day-ahead cycle retrieved from the study day-ahead interval. The capacity matching attribute for a given day-ahead interval is defined as the ratio of the square root of averaged squared deviations between average real-time bid and cleared day-ahead bid for all day-ahead intervals of past day-ahead cycle, over maximal day-ahead bid within the past day-ahead cycle retrieved from the study interval:

$$A_h^{\text{capacity\_matching}} = \frac{\sqrt{\frac{1}{N_h}\sum_{h'=\mathbf{0}}^{N_h-1}\left(\Delta P_{h-h'}^{RT-DA}\right)^{\mathbf{2}}}}{\overline{P}_h^{DA}} \tag{7}$$

The fourth characteristic measure is an up-ramping shortage attribute, $A_h^{upramp\_short}$ is used to measure the difference between ramp-up rates for cleared day-ahead and average actual real-time bid during ramping up intervals over the monitoring window. The up-ramping shortage attribute for a given day-ahead interval, $A_h^{upramp\_short}$ is defined as the ratio of the accumulated incremental power deviation, $\Delta^2 P_{h-h'}^{RT-DA}$ for all common day-ahead intervals between the up-ramping period and the monitoring window, over maximal day-ahead bid within the past day-ahead cycle:

$$A_h^{upramp\_short} = \frac{\sum_{h'=\mathbf{0}}^{\mathrm{W}-1}\left[0.5+0.5sgn(P_{h-h'}^{DA}-P_{h-h'-1}^{DA})\right]\max\left(\mathbf{0},\Delta^2 P_{h-h'}^{RT-DA}\right)}{\overline{P}_h^{DA}} \tag{8}$$

The incremental power deviation $\Delta^2 P_{h-h'}^{RT-DA}$is defined as the difference between incremental power change of cleared day-ahead bid and incremental power change of average real-time bid for a power producer as shown in (9a), and as ones the difference between incremental power change of average real-time bid and incremental power change of cleared day-ahead bid for a power consumer as shown in (9b):

$$\Delta^2 P_{h-h'}^{RT-DA} = (P_{h-h'}^{DA} - P_{h-h'-1}^{DA}) - (\hat{P}_{h-h'}^{RT} + \hat{P}_{h-h'-1}^{RT}) \tag{9a}$$

$$\Delta^2 P_{h-h'}^{RT-DA} = (\hat{P}_{h-h'}^{RT} - \hat{P}_{h-h'-1}^{RT}) - (P_{h-h'}^{DA} + P_{h-h'-1}^{DA}) \tag{9b}$$

The up-ramping period for the study day-ahead interval h is defined as the set of day-ahead time intervals that the cleared day-ahead bid at a given day-ahead interval is greater than ones at previous day-ahead interval.

The fifth characteristic measure is a down-ramping shortage attribute, $A_h^{dnramp\_short}$ which is used to measure the difference between ramp-down rates for cleared day-ahead and average actual real-time bid during ramping down intervals over the monitoring window. The down-ramping shortage attribute for a given day-ahead interval, $A_h^{dnramp\_short}$ is defined as the ratio of the accumulated decremental power deviation, $(-\Delta^2 P_{h-h'}^{RT-DA})$ for all common day-ahead intervals between the down-ramping period and the monitoring window, over maximal day-ahead bid within the past day-ahead cycle retrieved from the study interval:

$$A_h^{dnramp\_short} = \frac{\sum_{h'=\mathbf{0}}^{\mathrm{W}-1}\left[0.5+0.5sgn(P_{h-h'-1}^{DA}-P_{h-h'}^{DA})\right]\max\left(\mathbf{0},-\Delta^2 P_{h-h'}^{RT-DA}\right)}{\overline{P}_h^{DA}} \tag{10}$$

The down-ramping period for the study day-ahead interval h is defined as the set of day-ahead time intervals that the cleared day-ahead bid at a given day-ahead interval is lower than ones at previous day-ahead interval..

The sixth characteristic measure is a ramping matching attribute, $\boldsymbol{A}_h^{ramp\_matching}$ which is used to measure the difference between ramping rates of cleared day-ahead and average actual real-time bid over past day-ahead cycle. The ramping matching attribute is normalized with the maximum day-ahead bid over a period of past day-ahead cycle. The ramping matching attribute for a given day-ahead interval is defined as the ratio of the square root of averaged squared incremental power deviations between average real-time bid and cleared day-ahead bid for all day-ahead intervals of past day-ahead cycle over maximal day-ahead bid within the past day-ahead cycle retrieved from the study interval, according to:

$$A_h^{\text{ramp\_matching}} = \frac{\sqrt{\frac{1}{N_h}\sum_{h'=\mathbf{0}}^{N_h-1}\left(\Delta^2 P_{h-h'}^{RT-DA}\right)^{\mathbf{2}}}}{\overline{P}_h^{DA}} \tag{11}$$

The seventh characteristic measure is a cross-market correlation attribute, $\boldsymbol{A}_h^{correlation}$ which is used to measure the correlation between cleared day-ahead bid and average actual real-time bid over past day-ahead cycle, according to:

$$A_{\mathrm{h}}^{correlation} = \frac{N_h\sum_{h'=\mathbf{0}}^{N_h-1}\hat{P}_{h-h'}^{RT}P_{h-h'}^{DA}-\sum_{h'=\mathbf{0}}^{N_h-1}\hat{P}_{h-h'}^{RT}\sum_{h'=\mathbf{0}}^{N_h-1}P_{h-h'}^{DA}}{\sqrt{\left[N_h\sum_{h'=\mathbf{0}}^{N_h-1}(\hat{P}_{h-h'}^{RT})^{\mathbf{2}}-\left(\sum_{h'=\mathbf{0}}^{N_h-1}\hat{P}_{h-h'}^{RT}\right)^{\mathbf{2}}\right]\left[N_h\sum_{h'=\mathbf{0}}^{N_h-1}(P_{h-h'}^{DA})^{\mathbf{2}}-\left(\sum_{h'=\mathbf{0}}^{N_h-1}P_{h-h'}^{DA}\right)^{\mathbf{2}}\right]}} \tag{12}$$

This attribute can also be defined and used for measuring the correlation of activities between different market participants based on cleared day-ahead and/or actual average real-time bid over past day-ahead cycle.

The eighth characteristic measure is an environmental impact attribute, $A_h^{env-impact}$ which is used to measure the impacts of severe weather, holiday and special events, equipment forced and scheduled outages on the mismatches between the cleared day-ahead and actual average real-time bid over past day-ahead cycle. For a power consumer, $A_h^{env-impact}$ can be determined based on the weather information, such as temperature-humidity-index:

$$A_h^{env-impact} = A_{\mathrm{h}}^{dtype}A_h^{thi} \tag{13}$$

where A_{h}^{dtype} is the scale factor defined for holidays and special events, A_h^{thi} is an attribute representing the impacts of severe weather and defined as:

$$A_h^{thi} = \frac{\sqrt{\frac{1}{\mathrm{W}}\sum_{h'=\mathbf{0}}^{\mathrm{W}-1}\widehat{THI}_{h-h'}^2}}{\max\limits_{h'=\{\mathbf{0},\mathbf{1},\cdots,N_h-\mathbf{1}\}}\widehat{THI}_{h-h'}} \tag{14}$$

$\widehat{THI}_h$ is a temperature-humidity index (THI) to account for the combined effects of environmental temperature and relative humidity. For a power producer, $A_h^{env-impact}$ can be determined based on the fuel availability A_{h}^{fuel} and equipment availably A_{h}^{equip} as:

$$A_h^{env-impact} = A_{\mathrm{h}}^{equip}A_{\mathrm{h}}^{fuel} \tag{15}$$

A_{h}^{fuel} may be weather related, and A_{h}^{equip} depends on equipment scheduled outage and random faults. The attribute $A_h^{env-impact}$ can also be set by operator manually to include any impacts that not defined here.

III. Illegitimate Trade Feature Sample Generation and Illegitimate Type Labeling

According to the trade features defined in above section, we can create a set of legitimate trade feature samples using historical trade profiles. Based on those legitimate feature samples, we can generate a set of illegitimate trade feature samples using a negative selection procedure, and assign a specific illegitimate trade type for each illegitimate trade feature sample using an illegitimate trade type labeling procedure discussed in this section. In this paper, a genetic algorithms-based negative selection procedure [7] is employed.

The genetic algorithms-based negative selection procedure for generating illegitimate trade feature samples includes the following steps:

- Step 1: define the representative legitimate feature trade samples based on historical trading profiles obtained from day-ahead and real-time markets.
- Step 2: initialize a population of illegitimate trade feature samples using negative selection procedure.
- Step 3: create new population of illegitimate trade feature samples using the genetic algorithms.
- Step 4: combine the illegitimate trade feature samples from both Step 2 and Step 3 together, and retain the ones with top fitness to keep the population size fixed in each generation.
- Step 5: repeat Step 3 to Step 4 until the minimal radius of illegitimate trade feature samples is less than a preset threshold.

Step 1 of above procedure first calculates the trade feature attributes for each legitimate trade set using formulas in Section II, then convert each feature from floating number into integer ones to enable using integer number based genetic algorithms for fast computation. For any j-th feature attribute A_h^j, it is converted into an integer value between 1 and bound integer number B^j, $\breve{A}_h^j$, according to:

$$\breve{A}_h^j = \text{int}\left[\frac{\left(A_h^j-\underline{A}_h^j\right)B^j+\left(\overline{A}_h^j-A_h^j\right)}{\overline{A}_h^j-\underline{A}_h^j}\right] \tag{16}$$

$\overline{A}_h^j$ and $\underline{A}_h^j$ are the possible maximum and minimum values of A_h^j. After that a set of representative legitimate feature trade samples can be defined. Suppose there are N legitimate feature samples available $\mathbf{x}_i^C (i = 1,2,\cdots,N)$, with centers $\mathbf{O}_i^C$, and radiuses r_i^C. $\mathbf{O}_i^C$ is defined by set of scaled integer trade features, $\mathbf{O}_i^C = [A_{i1}^C, A_{i2}^C, \cdots, A_{iL}^C]$. If the number of available trade profiles is limited, we can directly use each trade profile to define one legitimate sample by setting its center using associated trade features of the trade profile, and its radius using a pre-set threshold. If the number of available trade profiles is sufficient enough, we can use k-means clustering method to partition available trade profiles into N clusters and use trade features of each cluster to define one legitimate sample and set its center and radius based on the statistics of trade features of all trade profiles in the cluster.

In Step 2, the candidate illegitimate trade feature samples are randomly generated, and compared with the legitimate trade feature sample set generated in Step 1. Only those samples that do not match any element of the legitimate sample set are retained. Assumed there are M illegitimate samples $\mathbf{x}_i^W (i = 1,2,\cdots,M)$ to be generated, with centers $\mathbf{O}_i^W$, and radiuses r_i^W, and the center $\mathbf{O}_i^W$ is defined by set of scaled integer trade features, $\mathbf{O}_i^W = [A_{i1}^W, A_{i2}^W, \cdots, A_{iL}^W]$, and $A_{ij}^W (j = 1,2,\cdots,L)$ is set randomly among 1 and the integer bound number for the j-th feature, B^j .The radius of illegitimate sample i, r_i^W is defined based on its Euclidean distance to nearest legitimate sample k, according to:

$$\mathrm{r}_i^W = \left\|\mathbf{O}_k^C - \mathbf{O}_i^W\right\|_{L_2} - \mathrm{r}_k^C \tag{17}$$

$\mathbf{O}_k^C$ and r_k^C are the center and radius of its nearest legitimate sample k, i.e.

$$\left\|\mathbf{O}_k^C - \mathbf{O}_i^W\right\|_{L_2} = \min_{j\in[1,2,\ldots,N]} \left\|\mathbf{O}_j^C - \mathbf{O}_i^W\right\|_{L_2} \tag{18}$$

$\left\|\mathbf{O}_k^C - \mathbf{O}_i^W\right\|_{L_2}$ and $\left\|\mathbf{O}_j^C - \mathbf{O}_i^W\right\|_{L_2}$ represent the Euclidean distances between $\mathbf{O}_k^C$ and $\mathbf{O}_i^W$ and $\mathbf{O}_j^C$ and $\mathbf{O}_i^W$, respectively, as shown below:

$$\left\|\mathbf{O}_k^C - \mathbf{O}_i^W\right\|_{L_2} = \sqrt{\sum_{l=1}^L (A_{kl}^C - A_{il}^W)^2} \tag{19}$$

$$\left\|\mathbf{O}_j^C - \mathbf{O}_i^W\right\|_{L_2} = \sqrt{\sum_{l=1}^L \left(A_{jl}^C - A_{il}^W\right)^2} \tag{20}$$

If there exists legitimate sample j, such that $\left\|\mathbf{O}_j^C - \mathbf{O}_i^W\right\|_{L_2} \le \mathrm{r}_j^C$, this illegitimate sample j becomes invalid, since it indeed overlaps with a legitimate sample j.

In Step 3, the generated candidate illegitimate samples in Step 2 are further optimized to avoid overlapping with legitimate samples and maximize candidate sample coverage radius. Doing so, any illegitimate sample i generated in this way has the maximal possible radius r_i^W without any overlapping with all the N legitimate samples. We first apply the crossover operator on the current population to create new population, then apply mutation operator to the newly created population to add more stochastic variations. Mutation is used to introduce variations into the trade feature bit-strings through replacing random bits of the bit-strings with their complementary values. Crossover is used to merge two bit-strings to produce new sample containing certain subparts from two existing samples. Based on the determined centers for new population, we can determine corresponding radiuses for those new illegitimate samples by using (17), accordingly.

In Step 4, only the most fitted illegitimate samples have the possibility of survival in the next generation. We define the fitness of each illegitimate sample candidate by using its radius r_i^W, as calculated in (17). That is to say, those illegitimate samples with larger valid radiuses have higher fitness for evolution in the Genetic Algorithms. When the procedure is converged, the integer number represented features for each illegitimate feature samples are converted back int floating ones, according to:

$$A_h^j = \frac{\left(\overline{A}_h^j-\underline{A}_h^j\right)\breve{A}_h^j+\left(\underline{A}_h^j B^j-\overline{A}_h^j\right)}{\left(B^j-1\right)} \tag{21}$$

After a certain number of qualified illegitimate samples are generated by such genetic algorithm based negative selection procedure, a set of predetermined illegitimate trade labels can be assigned to each illegitimate sample, and then those samples can be used to detect the legitimacy status for the incoming trades.

The procedure for labeling illegitimate trade type to illegitimate feature samples includes the following steps

- Step 1: generate at least one exemplar trade profile for each pre-defined illegitimate trade type through simulating the specific trading scenario defined for the given illegitimate trade type.
- Step 2: determine corresponding trade features for each exemplar illegitimate trade profiles, and create a set of typical illegitimate feature samples with specified illegitimate trade type.
- Step 3: assign the illegitimate type of the nearest typical illegitimate feature sample to any generated illegitimate trade feature sample as its illegitimate type based on Chebyshev distance.

Assumed there are T typical illegitimate feature samples available, $\mathbf{x}_i^{TW} (i = 1,2,\cdots,T)$ with centers $\mathbf{O}_i^{TW}$ that defined by set of trade features, $\mathbf{O}_i^{TW} = [A_{i1}^{TW}, A_{i2}^{TW}, \cdots, A_{iL}^{TW}]$. The illegitimate sample $\mathbf{x}_i^W$ is assigned the illegitimate type of the nearest typical illegitimate sample $\mathbf{x}_k^{TW}$ measured by Chebyshev distance, i.e.

$$\left\|\mathbf{O}_k^{TW} - \mathbf{O}_i^W\right\|_{L_\infty} = \min_{j\in[1,2,\ldots,T]} \left\|\mathbf{O}_j^{TW} - \mathbf{O}_i^W\right\|_{L_\infty} \tag{22}$$

where $\left\|\mathbf{O}_k^{TW}-\mathbf{O}_i^{W}\right\|_{L_\infty}$ and $\left\|\mathbf{O}_j^{TW}-\mathbf{O}_i^{W}\right\|_{L_\infty}$ represent the Chebyshev distances between $\mathbf{O}_k^{TW}$ and $\mathbf{O}_i^{W}$ and $\mathbf{O}_j^{TW}$ and $\mathbf{O}_i^{W}$, respectively, as shown below:

$$\left\|\mathbf{O}_k^{TW}-\mathbf{O}_i^{W}\right\|_{L_\infty} = \max_{i=1,\cdots,L}\left|A_{jl}^{TW}-A_{il}^{W}\right| \quad (23)$$

$$\left\|\mathbf{O}_j^{TW}-\mathbf{O}_i^{W}\right\|_{L_\infty} = \max_{i=1,\cdots,L}\left|A_{jl}^{TW}-A_{il}^{W}\right| \quad (24)$$

IV. Across-Market Illegitimate Trade Detection

A feedforward neural network (FNN) is used for modeling the multiple-class trade classification function. The FNN implicitly represent the relationship between the trade types and the monitored trade feature attributes determined based on the cleared day-ahead bids, the actual real-time bids, and environment conditions.

The FNN consists of one input layer, L hidden layer, and one output layer [8]. It takes the trade type as the outputs, and trade feature attributes as inputs. The input layer consists 8 input units to receive the eight different features for trading activities, including peak shortage attribute, valley excess attribute, capacity matching attribute, up-ramp shortage attribute, down-ramp shortage attribute, ramp matching attribute, cross-market correlation attribute, and environment impact attribute. The output layer consists a set of output units, in which each unit corresponds to one trade type, and its output is between 0 and 1. For example, if we consider 1 legitimate type, 4 different illegitimate types such as peak hour manipulation, valley hour manipulation, up-ramping period manipulation, and down-ramping period manipulation.. Then the output layer has 5 units. The output value with the largest value will be taken as the type predicted by the model.

The FNN has multiple hidden layers, and each layer contains multiple hidden units. The hidden layer l takes an input vector $\boldsymbol{x}_t^{[l]}$, and computes a (hidden) output vector $\boldsymbol{h}_t^{[l]}$according to:

$$\boldsymbol{h}_t^{[l]} = \mathrm{relu}\left(\boldsymbol{W}^{[l]}\boldsymbol{x}_t^{[l]} + b^{[l]}\right) \quad (25)$$

where $\mathrm{relu}(\cdot)$ denotes a rectified linear unit function that is applied element-wise, $\boldsymbol{W}^{[l]}$ is a weight matrix, and $b^{[l]}$ is a bias vector. Note that the output vector of one hidden layer is the input vector for the next hidden layer, i.e., $\boldsymbol{x}^{[l+1]} = \boldsymbol{h}^{[l]}$, except the last hidden layer, the output of which is mapped to the output through a nonlinear unit as follows:

$$\boldsymbol{y}_t = \mathrm{softmax}\left(\boldsymbol{W}h^{[L]} + \boldsymbol{b}\right) \quad (26)$$

where the output of j-th output unit is $y_{tj} = e^{\boldsymbol{W}_j h^{[L]}+\boldsymbol{b}_j} / \sum_k e^{\boldsymbol{W}_k h^{[L]}+\boldsymbol{b}_k}$, $\boldsymbol{W}$ is a weight matrix related output with last hidden layer, and $\boldsymbol{b}$ is a bias vector for the output layer.

The multi-layer FNN is trained using Adam optimization [9] which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments, such that the mean squared error between the predicted output $\boldsymbol{y}_t$ and the true value $\boldsymbol{d}_t$ is minimized, i.e., by minimizing the following loss function, ℓ':

$$\ell' = \frac{1}{m^{tr}}\sum_{i=1}^{m^{tr}}\sum_j\left(y_{tj}-d_{tj}\right)^2 \quad (27)$$

where, m^{tr} is the total number of samples for FNN training. After trained using a set of training samples, the multi-layer FNN can be used to determine if a trading activity is legitimate or belongs to which illegitimate type when the associated trade feature attributes are given.

V. Numerical Examples

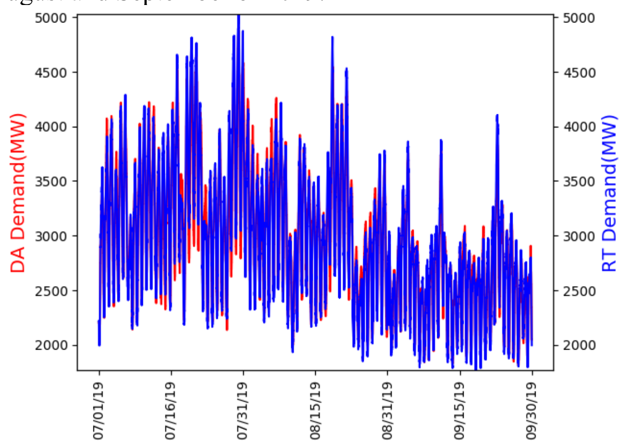
The proposed algorithm has been tested using a load serving entity scenario based on actual trade profiles for a load zone at Northeast Massachusetts and Boston area and historical weather observations at Boston station. The original trade profiles are obtained from New England ISO [10], and modified to represent illegitimate trade scenarios for facilitating algorithm testing.

The trade profiles include cleared day ahead hourly demands, and executed real time 5-minute demands of the load zone, in which day-ahead demands are actual bids, but the real-time demands are derived based on actual hourly zonal demands and the actual five-minute system demands. The weather information [11] includes hourly dry-bulb and dewpoint temperature observations. The hourly temperature-humidity index is used to represent weather condition that derived based on hourly dewpoint temperature and dry-bulb temperature observed at the weather station. The average THI for day-ahead interval h, $\widehat{THI}_h$ is defined as:

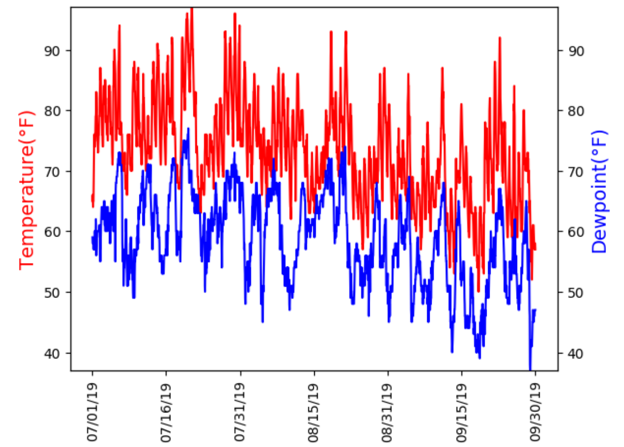
$$\widehat{THI}_h = 15 + 0.5 * \widehat{T}_\mathrm{h} + 0.3 * \widehat{H}_\mathrm{h} \quad (28)$$

$\widehat{T}_\mathrm{h}$ and $\widehat{H}_\mathrm{h}$ are the average real time temperature and dewpoint for the day-ahead interval h.

The trade activities and weather conditions for three months of 2019 are used, in which the data sets of July and August of 2019 are used to train the illegitimate trade detection model, and the ones in September of 2019 are used for testing the performance of the model. Fig. 1 gives the plots of trade profiles and weather observations for July, August and September of 2019.



(a). trade profiles



(b). weather observations

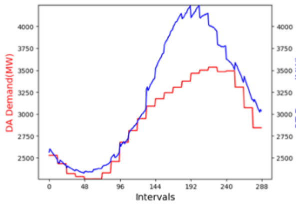
Fig. 1 Trade profiles and weather observations for July, August and September of 2019.

The real-time trade profiles for September of 2019 were modified to include the simulated illegitimate trading events as listed in Table I.

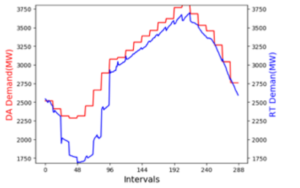
We have modeled 4 typical illegitimate trade scenarios, including anomaly peak (i.e. peak hour manipulation), anomaly valley (i.e. valley hour manipulation), anomaly up-ramp (i.e. up-ramping period manipulation), and anomaly down-ramp (i.e. down-ramping period manipulation). Fig.2 gives the plots for examples of typical illegitimate trade samples.

Table I. Added simulated illegitimate trading events

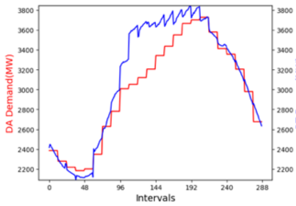
Illegitimate Type	Date	Period
Anomaly Peak	9/9/2019	11:00-19:00
	9/18/2019	15:00-20:00
Anomaly Up-Ramp	9/1/2019	7:00-13:00
	9/21/2019	8:00-14:00
Anomaly Valley	9/7/2019	1:00-8:00
	9/15/2019	2:00-8:00
Anomaly Down-Ramp	9/12/2019	18:00-19:00
	9/26/2019	18:00-23:00



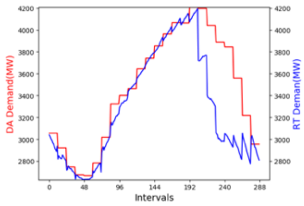
(a). Anomaly Peak



(b). Anomaly Valley



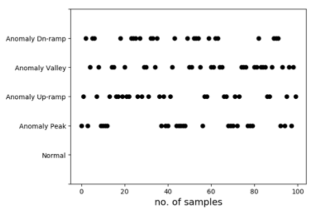
(c). Anomaly Up Ramping



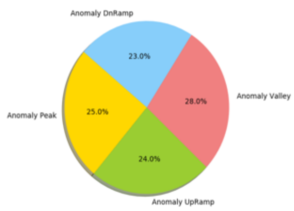
(d). Anomaly Down Ramping

Fig. 2 Examples of typical illegitimate trade samples

Fig. 3 listed the scatter and pie plots for the statistics of generated illegitimate trade feature samples with different illegitimate trade types based on trade profiles of July and August of 2019. The radius of legitimate feature sample is set as 0.06, and the number of illegitimate feature samples is set as 100. The length of monitoring window is 6 hours.



(a). sample distribution



(b). sample statistics

Fig. 3 The statistics of generated illegitimate trade feature samples

The multiple-layer forward neural network is used, in which 3 hidden layers are configured with 32, 64 and 32 units, respectively. The output layer contains 5 units with Softmax activation functions.

The test results for trade legitimacy identification and trade type labelling of trading activities are listed in Tables II and III.

Table II. Overall summary of testing results

Case Type	Total counts	Estimate counts		Accuracy (%)
		Legitimate	Illegitimate	
All	912	/	/	95.50
Legitimate cases	859	826	33	96.16
Illegitimate cases	53	8	45	84.91

Table II lists the statistics of trade legitimacy detection results for all hourly intervals in September of 2019. As showed in the table, 96.16 % of legitimate cases are correctly labeled as legitimate, and 84.91% of illegitimate cases are correctly identified as illegitimate. The overall accuracy for legitimacy identification is 95.50%.

Table III lists the statistics of detection results for each trade type for all hourly intervals in September of 2019. The symbols "NM","AP","AV","AU", and "AD" represent different trade types for the trading cases, including legitimate ("NM"), anomaly peak("AP"), anomaly valley("AV"), anomaly up-ramp ("AU"), and anomaly down-ramp ("AD"). Although different type of scenarios may have different prediction accuracy, the overall labelling accuracy is quite promising, i.e. 94.63%. It is worthy to note that this accuracy can be further improved by tuning typical feature samples to make them more distinct from each other.

Table III. Classified summary of testing results

Case Type	Total Counts	Total Fails	Estimate counts					Accuracy (%)
			NM	AP	AU	AV	AD	
All	912	49	/					94.63
NM	859	33	**826**	7	22	3	1	96.16
AP	16	4	3	**12**	1	0	0	75.00
AU	14	7	2	4	**7**	0	1	50.00
AV	15	3	1	0	0	**12**	2	80.00
AD	8	2	2	0	0	0	**6**	75.00

VI. Conclusions

A novel detection algorithm has been proposed for detecting trade activities suspected to be illegitimate across day-ahead and real-time energy markets.

Illegitimate trades are detected by using a mathematical model relating the trading legitimacy status with a set of trade feature attributes which represents the similarity between day ahead and real-time demands and the impacts of environmental changes. The model is trained using a set of legitimate and illegitimate trading feature samples. The illegitimate trading feature samples are generated based on legitimate feature samples by using a genetic-algorithms based negative selection approach, and labeled with specific illegitimate types based on predefined typical feature attribute samples. The legitimate trading feature samples are determined based on actual day-ahead and real-time trade profiles. The proposed algorithm solely relies on historical trade profiles, and does not require any illegitimate trade data available.

The test results on sample trade profiles obtained from New England ISO have proven the effectiveness of the proposed algorithm.

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