

A Hybrid Feature Selection and Generation Algorithm for Electricity Load Prediction using Grammatical Evolution

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Abstract—Accurate load prediction plays a major role in devising effective power system control strategies. Successful prediction systems often use machine learning (ML) methods. The success of ML methods, among other things, depends on a suitable choice of input features which are usually selected by domain-experts. In this paper, we propose a novel systematic way of generating and selecting better features for daily peak electricity load prediction using kernel methods. Grammatical evolution is used to evolve an initial population of well performing individuals, which are subsequently mapped to feature subsets derived from wavelets and technical indicator type formulae used in finance. It is shown that the generated features can improve results, while requiring no domain-specific knowledge. The proposed method is focused on feature generation and can be applied to a wide range of ML architectures and applications.

Keywords—Load prediction; grammatical evolution; feature selection; context-free grammar; machine learning

I. INTRODUCTION

Electricity load prediction is the first phase in power system planning and control. While overestimation leads to an undesired spinning reserve and excess supply, underestimation causes insufficient reserve supply, implying higher costs. The inherent non-linear and non-stationary nature of electricity load time-series makes supervised machine learning (ML) methods more appealing for prediction than model-based approaches [1].

In a time-series prediction task, the ML algorithm is presented with training samples $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_n, y_n)$, where $\mathbf{x}_j \in \mathbb{R}^N$ is a vector of input features and $y_j \in \mathbb{R}$ is the target, e.g. daily peak electricity load. The learner has to infer a general function (a hypothesis) that can predict y_k for unseen \mathbf{x}_k . This generalization is achieved by searching a hypothesis space \mathcal{H} for a solution hypothesis $h \in \mathcal{H}$ that best fits the structure of the training samples. The performance of ML algorithm depends strongly on the formalism of h using different input feature vectors, \mathbf{x} .

The input features used in some electricity load prediction applications are summarised in Table I. In each case, the input features selected by human experts were similar with some overlap between different works. However, the choice is generally ad-hoc. It would therefore be useful to have a framework that can automatically generate and select useful features that have a meaningful interpretation.

A framework for function-based feature generation using context-free grammars was first proposed by Markovitch and Rosenstein [2]. Such grammars are used in linguistics to describe sentence structure and words of a natural language and in computer science to describe the structure of programming languages. Markovitch and Rosenstein generated features strongly related to the target using decision trees. Unfortunately, the technique was only suitable for problems where the features are apparent from the problem definition. In other related work, Eads et. al [3] and Pachet and Roy [4] addressed supervised time-series classification using genetic programming (GP) operators defined in a grammatical structure. GP was also used by Ritthof et. al [5] to combine feature generation and selection and applied to the interpretation of chromatography time-series.

Automatic feature generation can generate irrelevant and redundant features. Feature selection (FS) eliminates such features thereby improving the accuracy and speed of ML algorithms. Genetic algorithms have been used for FS as a so called wrapper to avoid enumerating the entire space [12]–[14]. Muni et. al. [15] proposed a GP based FS algorithm which evolved a population of classifiers to choose accurate classifiers with the minimum number of features. Multi-population GP has also been used in [16] to develop a method for simultaneous feature extraction and selection.

In this paper, we use a modified version of grammatical evolution (GE) [17] to generate and select parametrized features for peak electricity load prediction. Some of the generated features in this work use the concept of *technical indicators*, as used in finance. These are formulae that identify patterns and market trends in financial markets, developed from models for price and volume. To the best of our knowledge, this is the first time (i) GE is applied as a feature discovery technique in time-series prediction, and (ii) technical indicator type formulae are used for predicting

Table I: Common features in electricity load time-series prediction.

<ul style="list-style-type: none"> • Previous week's hourly load information • Temperature and calendar information 	[6]–[8]
<ul style="list-style-type: none"> • Previous load information and its differenced values • Daubechies wavelets and its differenced values 	[9], [10]
<ul style="list-style-type: none"> • EMD transform and its differenced values 	[11]

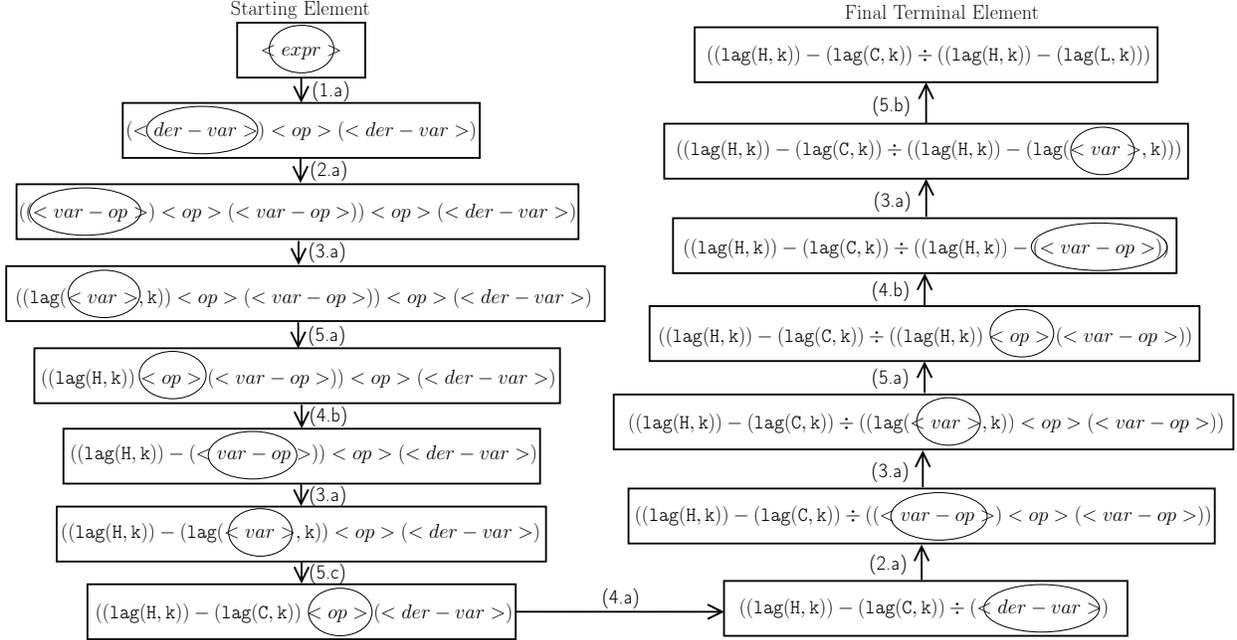


Figure 1: Feature generation using GE. The circles represent the leftmost non-terminal to apply the production rules on. The rules are chosen based on the MOD operator result on codons. If the first codon of the chromosome is 224, since the first non-terminal is $\langle expr \rangle$ and the number of rules available in grammar family 2 is 2, the rule is $(224) \text{ MOD } (2) = 0$, hence rule (1.a) is chosen, and so on.

electricity load time-series.

Define the solution hypothesis of a particular ML architecture formulated using expert suggested features h_1 and the solution hypothesis formulated using a feature subset discovered through the proposed framework h_2 . The main contribution of our work is to demonstrate that the prediction accuracy can be better with h_2 than with h_1 .

This paper is organized as follows. Sec. II provides a brief review of context-free grammar and GE. Sec. III presents the main part of our work on how grammar families are evolved to generate informative features. The results are given in Sec. IV and the performance of our approach is compared with other approaches. Finally, the paper is concluded with remarks for future work in Sec. V.

II. BACKGROUND

A. Context-free Grammar

A context-free grammar (CFG) is used to generate patterns and strings using hierarchically organized production rules [18]. Using the Backus-Naur form (BNF), a CFG can be described by the tuple $(\mathcal{T}, \mathcal{N}, \mathcal{R}, \mathcal{S})$ where \mathcal{T} is a set of terminal symbols and \mathcal{N} is a set of non-terminal symbols with $\mathcal{N} \cap \mathcal{T} = \emptyset$. The non-terminal symbols in \mathcal{N} and terminal symbols in \mathcal{T} are the lexical elements used in specifying the production rules of a CFG. A non-terminal symbol is one that can be replaced by other non-terminal and/or terminal symbols. Terminal symbols are literals that symbols in \mathcal{N} can take. A terminal symbol cannot be altered by the grammar rules \mathcal{R} , a set of relations (also referred to

as production rules) in the form of $\mathcal{R} \rightarrow \alpha$ with $\mathcal{R} \in \mathcal{N}$, $\alpha \in (\mathcal{N} \cup \mathcal{T})$. $\mathcal{S} \in \mathcal{N}$ is the start symbol. If rules are defined as $\mathcal{R} = \{x \rightarrow xa, x \rightarrow ax\}$, a is a terminal symbol since no rule exists to change it, and x is a non-terminal symbol.

B. Grammatical Evolution

GE is a grammar-guided GP technique, which has been used in computational finance, credit rating & corporate failure prediction, music and robot control applications (refer to [19] for a survey). GE can be used to evolve complete programs in an arbitrary language. Similar to GP, GE evolves a population towards a certain goal. GE performs evolutionary operations on integer individuals which are then mapped using the defined grammar to feature subsets; on the other hand GP directly operates on the actual program's tree structure [17]. In GE, a suitable grammar developed for the problem at hand is specified in BNF. A chromosome is represented as an integer string, with each integer creating a *codon*. The codon values are then used to select production rules from the grammar definition using the modulus (MOD) operator. A group of codons which is used to create a feature is called a *gene*. Detailed explanation on GE can be found in [17] and is omitted here for space. Fig. 1 illustrates how the grammar family 2 in Table II can generate a feature. With C lagged by $k = 1$ and L and H lagged by $k = 0$, we obtain $(H_t - C_{t-1}) / (H_t - L_t)$. This formula is popular as the accumulation/distribution oscillator which is a widely used technical indicator by financial analysts. The proposed grammar can produce many such popular indicators.

III. METHODOLOGY

Fig. 2 shows the proposed architecture. Chromosomes are selected from the population which are then mapped to feature subsets using CFG in Tables II and III. These subsets are evaluated and best feature subsets are selected by a wrapper approach. The population is evolved such that the learner architecture has a minimum mean cross validation error on randomized samples drawn from a validation set.

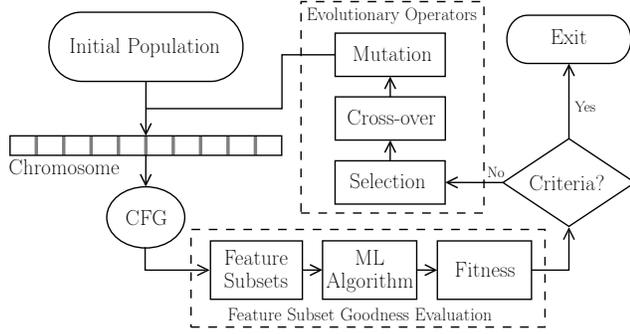


Figure 2: The architecture of the prediction system.

A. Grammar Definition

The grammar families in Table II can generate *trend*, *momentum* and *volatility* type indicators. This grammar construction was inspired by 30 common technical indicators. A single grammar capable of generating all the features generated by the grammar families can be designed but such a grammar would have many production rules, leading to a large search space and long computational times. In the financial literature, data is represented by H, L and C which are the daily highest, lowest and closing (last) prices. The upward and downward price changes are $U = \max(0, H_t - H_{t-1})$ and $D = \min(0, H_t - H_{t-1})$, H_t is the current time-sample highest price. In this paper, the same notation is adapted to half-hourly electricity load data, with the daily high, low and close electricity load used in place of price. The basic operators lag, abs, diff and delat respectively refer to lagged (x_{t-k}) , absolute $(|x_t|)$, first difference $(\Delta x = x_t - x_{t-1})$ and the relative first difference values $((x_t - x_{t-1})/x_t)$ of a time-series where x_t is the load at time t and k is a constant. The operators ema, sma, max, min, sd, meandev and histwin extract the exponential moving average, simple moving average, maximum, minimum, standard deviation, mean deviation and a history sequence for a moving window of size n .

The discrete wavelet transform is widely used as a multi-resolution decomposition technique which can elucidate otherwise hidden relationships in non-stationary time-series like electricity load data. We perform the maximal overlap discrete wavelet transform using the Daubechies mother wavelet. For a time-series $x(k)$ with N samples, each resolution scale would have N samples for each level,

enabling the usage of wavelet coefficients as features. The m -level wavelet decomposition coefficients of $x(k)$ are $D_j(k)$ and $S_j(k)$, $j = 1, 2, \dots, m$. The D coefficients capture local fluctuations and S are smoothed (trend) versions at each scale. The m^{th} level wavelet decomposition of a time-series is then given by: $\mathbf{D}^m = \sum_{i=0}^m D^m(k+i)$ and $\mathbf{S}^m = \sum_{i=0}^m S^m(k+i)$. The grammar in Table III uses wavelets. H is the maximum daily electricity load time-series. D^1, D^2, D^3 and $S = S^3$ are the 3-level decomposition components of H. Empirical mode decomposition (EMD) is an alternative to wavelets but an EMD based grammar was not used for this paper.

Table II: High, low, close electricity load multi-family grammar.

Grammar family 1 (moving average)	
$\mathcal{N} = \{expr, der-var, base-var, pre-op, base-op, var\}$	
$\mathcal{T} = \{\div, \text{delt}, \text{diff}, \text{ema}, \text{sma}, \text{max}, \text{min}, \text{meandev}, H, L, C, n, (,)\}$	
$S = \langle expr \rangle$	
\mathcal{R} Production rules	
$\langle expr \rangle$	$::= ((expr) \div (expr)) \mid \langle der-var \rangle \mid \langle base-var \rangle$ (1.a), (1.b), (1.c)
$\langle der-var \rangle$	$::= \langle pre-op \rangle (\langle base-var \rangle, n)$ (2.a)
$\langle base-var \rangle$	$::= \langle base-op \rangle (\langle var \rangle) \mid \langle pre-op \rangle (\langle var \rangle, n) \mid \langle var \rangle$ (3.a), (3.b), (3.c)
$\langle pre-op \rangle$	$::= \text{ema} \mid \text{sma} \mid \text{max} \mid \text{min} \mid \text{meandv}$ (4.a), (4.b), (4.c), (4.d), (4.e)
$\langle base-op \rangle$	$::= \text{delt} \mid \text{diff}$ (5.a), (5.b)
$\langle var \rangle$	$::= H \mid L \mid C$ (6.a), (6.b), (6.c)
Grammar family 2 (momentum)	
$\mathcal{N} = \{expr, der-var, var-op, op, var\}$	
$\mathcal{T} = \{\div, -, \text{lag}, \text{ema}, U, D, H, L, C, n, k, (,)\}$	
$S = \langle expr \rangle$	
\mathcal{R} Production rules	
$\langle expr \rangle$	$::= \langle der-var \rangle \div \langle der-var \rangle$ (1.a)
$\langle der-var \rangle$	$::= \langle var-op \rangle (op) \langle var-op \rangle \mid \langle var-op \rangle$ (2.a), (2.b)
$\langle var-op \rangle$	$::= \text{lag}(\langle var \rangle, k) \mid \text{ema}(\langle var \rangle, n)$ (3.a), (3.b)
$\langle op \rangle$	$::= \div \mid -$ (4.a), (4.b)
$\langle var \rangle$	$::= H \mid L \mid C \mid U \mid D$ (5.a), (5.b), (5.c), (5.d) (5.e), (5.f)
Grammar family 3 (volatility)	
$\mathcal{N} = \{expr, var-op, var\}$	
$\mathcal{T} = \{+, -, \text{abs}, \text{sma}, \text{sd}, H, L, C, n, (,)\}$	
$S = \langle expr \rangle$	
\mathcal{R} Production rules	
$\langle expr \rangle$	$::= \text{sma}(\langle var-op \rangle, n) + \text{sd}(\langle var-op \rangle)$ (1.a)
	$\mid \text{sma}(\langle var-op \rangle, n) - \text{sd}(\langle var-op \rangle)$ (1.b)
$\langle var-op \rangle$	$::= \text{abs}(\langle var \rangle) \mid \langle var \rangle$ (2.a), (2.b)
$\langle var \rangle$	$::= H-L \mid H-C \mid C-L \mid H$ (3.a), (3.b), (3.c), (3.d)

B. Feature Generation

Feature generation is guided through GE. Each chromosome is dissected to 25 genes where each gene is considered a feature and GE is applied independently on each gene. To have a good mix of trend, momentum and volatility type formulae in HLC grammar, the first 10 gene partitions were

Table III: Wavelet based grammar.

$\mathcal{N} = \{expr, der-var, base-var, pre-op, base-op, var\}$		
$T = \{abs, delt, diff, lag, sma, sd, meandev, histwin, H, D^1, D^2, D^3, S, n, k, (,)\}$		
$S = \langle expr \rangle$		
\mathcal{R} Production rules		
$\langle expr \rangle$	$::= histwin(\langle base-var \rangle, n)$	(1.a)
	$\langle der-var \rangle$	(1.b)
	$\langle base-var \rangle$	(1.c)
$\langle der-var \rangle$	$::= \langle pre-op \rangle(\langle base-var \rangle, n)$	(2.a)
$\langle base-var \rangle$	$::= \langle base-op \rangle(\langle var \rangle)$	(3.a)
	$lag(\langle var \rangle, k)$	(3.b)
	$\langle pre-op \rangle(\langle var \rangle, n)$	(3.c)
$\langle pre-op \rangle$	$::= sma sd meandev$	(4.a), (4.b), (4.c)
$\langle base-op \rangle$	$::= delt diff abs$	(5.a), (5.b), (5.c)
$\langle var \rangle$	$::= H D^1 D^2 D^3 S$	(6.a), (6.b), (6.c), (6.d), (6.e)

mapped to the moving average grammar family, the next 10 to the momentum family and the final 5 to the volatility family. A single grammar was used for wavelet based feature generation with no such gene mapping.

Individuals were selected for recombination using fitness proportionate selection (also known as roulette wheel selection). We employed random mutation and a modified version of multiple-point crossover, such that the crossover is performed across all individual genes (see Fig. 3). The chromosome is represented as set of stacked genes for clarity. This crossover ensures that inter-grammar-family crossover is avoided. Elite individuals, i.e. the chromosomes that rank best in each generation were passed directly to the next generation without mutation or crossover.

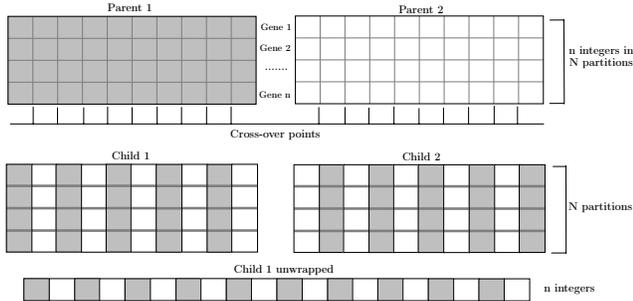


Figure 3: The proposed multiple-point crossover approach. A random number of crossover points at random locations are chosen.

We placed some specific chromosomes in the initial population which map to subsets of standard technical indicators such as disparity, momentum, stochastic oscillator (K), stochastic indicator (D), William’s oscillator (R), ROC (rate of convergence), RSI (relative strength index), CCI (commodity channel index) and moving averages. This ensured that the initial population was healthy and encouraged the generation of high performing feature subsets. The rest of the population consisted of randomly generated individuals. In making the final predictions, we also added calendar

information to the feature subset. Temperature information was not used since we investigated the effect of features derived from the time-series history itself.

C. Feature Subset Evaluation

The last step of the procedure was to evaluate the performance of a generated feature subset. Some of the generated features were parametrized by the window-size $n = 2, 3, 5, 7, 14$ and lag $k = 0, 1, 2, 3, 4, 5, 6, 7, 14$.

Algorithm 1 Feature subset evaluation procedure

Input current integer chromosome

- 1: Extract individual genes from the current chromosome
- 2: Map genes into grammar families (if necessary)
- 3: Derive symbolic features
- 4: Generate numeric feature subset Y_k for each time stamp
- 5: Append calendar information to Y_k (see Sec. IV)
- 6: **for** i in $1:N$ **do**
- 7: $err[i] =$ ML algorithm MAPE in validation sample i
- 8: **end for**
- 9: Calculate the average MAPE $e(Y_k) = \text{mean}(err)$
- 10: Calculate the final score $J(Y_k) = e(Y_k) + q(Y_k) + c(N_{NT})$

Output $J(Y_k)$

The feature subset evaluation steps are shown in Algorithm 1. The individuals with the lowest score were deemed to be the best. $e(Y_k)$ is the MAPE (mean absolute percentage error), given by $\frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|$ where n is the number of predictions, y is the target and \hat{y} is the predicted value. To choose robust features providing good generalization, the mean MAPE was calculated by the average error on $N = 15$ random samples of size 30 drawn from a validation dataset, e.g. the validation dataset Oct. 1998 - Dec. 1998 for predicting Jan. 1999. $q(\cdot)$ is an assessment of the symbolic feature expression complexity, taking into account the length, the number of operations and pre-operations. $c(\cdot)$ was calculated based on the number of non-terminal elements N_{NT} in subset Y_k (a subset containing many non-terminal elements was considered as poor).

IV. RESULTS

The EUNITE dataset [20] has been extensively used as a benchmark to test load prediction algorithms. It was originally published for a competition to predict the peak daily load for January 1999 using half-hourly recordings in the years 1997 and 1998.

In our approach, first the data was scaled to ensure that each feature was independently normalized. Calendar information was encoded as 7 binary values to represent the day-of-week and a single binary value for holidays as the competition winners in [6]. A self organising map (SOM) was used to identify data clusters using a peak load history window of 7 days, temperature and calendar information as

SOM inputs. This showed a very strong seasonality, dividing the data into *cold* and *hot* seasons (season 1 and 2 in Fig. 4 respectively). Based on the SOM result, we only used data from season 1 months to construct models in our experiments, e.g. to predict Jan. 1999, the model was constructed using Jan. 1997 - Mar. 1997, Oct. 1997 - Mar. 1998 and Oct. 1998 - Dec. 1998 data.

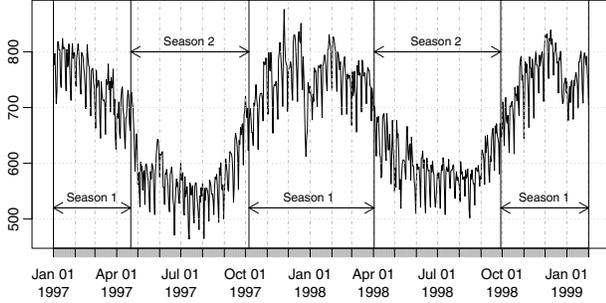


Figure 4: Clustering days to different seasons using a SOM.

Two different experiments were performed on the dataset. In the first trial, we used the wavelet based grammar in Table III in a month-ahead manner of prediction. Here, after predicting a load value for January 1st, 1999, we used this predicted value with the historical values before January 1st to predict January 2nd, 1999. This process was continued until the predicted load value of January 31st was obtained. For the second approach, we used the grammar in Table II. This requires the previous day's high, low and close values, and is more suited to a day-ahead prediction approach. Therefore, the actual historical HLC values are used in predicting each day.

For initial performance comparison, autoregressive integrated moving average (ARIMA) and exponential smoothing (ETS) models were chosen as analytical methods. Support vector machine (SVM) and kernel recursive least squares (KRLS) algorithm were used as kernel based ML methods. Table IV summarizes the results of the different techniques used for different feature subsets on different months. It was observed that the best results were produced by kernel methods with a radial basis kernel function parametrized by γ , i.e. $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$, where x_i, x_j are the input training vectors, $i, j = 1, 2, \dots, m$. As KRLS requires one less parameter (σ and λ) than SVM regression (C , γ and ϵ) consuming less hyper-parameter tuning time, KRLS was chosen for feature subset evaluation as explained in section III-C. The optimal parameters for the KRLS feature subset evaluator, $\sigma = 256$ and $\lambda = 0.0625$ were chosen by 10-fold repeated cross validation using a peak load history window of 7 days and encoded calendar information as features.

Based on the features used in previous load prediction work, we compared the performance of 5 domain-expert suggested feature subsets in Table IV and observed that the result stability for different months is poor, e.g. the feature subset $H_k, \Delta H_k, \Delta D_i^1, \Delta D_i^2, \Delta D_i^3, \Delta S_i (\forall i \in \{k-1, \dots, k-6\})$

performed remarkably well only in Jan. 1999 but the average accuracy was inferior to other subsets considered. We suspect that some related work on the EUNITE dataset have used specific subsets in a trial and error fashion to report good performance only on the *test* dataset, Jan. 1999.

A chromosome of the proposed GE algorithm comprised of 24 codons and 25 genes, i.e. a total 25 features with each feature represented by 24 codons making the integer chromosome size 600. The population size was 24 and 100 generations were iterated. The best 2 chromosomes in each generation were considered to be elite individuals.

10 GE trials were performed and the results are brought at the bottom of Table IV. The HLC based grammar produced significantly better results for each of the 3 months (1.15%, 1.73% and 1.39%), and even the worst performing HLC feature subset outperformed all other methods for average day-ahead predictions. Although the best wavelet feature subset (1.81%) outperformed other domain-expert suggested feature subsets for day-ahead predictions, the average performance of each month (1.96%) was poor. However, its performance for month-ahead prediction was promising. This leads us to state that the HLC grammar incorporates more information about the daily variations of load and significantly improves day-ahead predictions while the wavelet grammar elucidates long-term trends and hence is more suited for month-ahead predictions.

Table V compiles selected features from all GE trials filtered using the minimum-redundancy-maximum-relevance (mRMR) criterion. While some features are obvious and straightforward (e.g. ΔH , H , $\text{delt}(H)$, $\text{histwin}(H, 14)$),

Table V: Selected features from 10 GE runs.

HLC features	Wavelet features
1 $(C-L - L)/ C-L $	D_1
2 $(L - H-L)/L$	$\text{delt}(H)$
3 $(\text{ema}(\Delta C, 2))/(\text{ema}(\text{delt}(C), 2))$	ΔD_1
4 $(\text{ema}(H, 5))/(\min(\text{ema}(H, 2), 2))$	ΔH
5 $\text{delt}(H)$	ΔS
6 $\text{delt}(L)$	H
7 ΔH	$\text{lag}(D_3, 5)$
8 $\text{ema}(C, 3)$	$\text{lag}(\text{delt}(H), 2)$
9 $\text{ema}(C-L, 5) + \text{sd}(H-L, 3)$	$\text{lag}(\Delta D_1, 1)$
10 $\text{ema}(D, 3)$	$\text{lag}(\Delta D_3, 4)$
11 $\text{ema}(\text{ema}(H, 5), 3)$	$\text{lag}(\text{meandev}(D_1, 14), 3)$
12 $\text{ema}(H, 7)$	$\text{lag}(\text{sd}(H, 7), 3)$
13 $\text{ema}(H, 7) - \text{sd}(H-C, 2)$	$\text{lag}(S, 6)$
14 $\text{ema}(H-C, 2) + \text{sd}(H, 14)$	$\text{lag}(\text{sma}(D_1, 7), 6)$
15 $\text{ema}(\text{lag}(D, 7), 3)$	$\text{histwin}(\Delta H, 7)$
16 $\text{ema}(\text{lag}(U, 3), 3)$	$\text{lag}(\text{sma}(H, 5), 4)$
17 $\text{lag}(H, 7)$	$\text{histwin}(H, 14)$
18 $\text{lag}(U, 1)$	$\text{meandev}(D_1, 14)$
19 $\max(H, 14)$	$\text{sd}(D_1, 14)$
20 $\max(L, 3) - \text{lag}(H, 7)$	$\text{sd}(H, 14)$
21 $\max(\text{lag}(H, 1), 3)$	S
22 $\min(D, 5)$	$\text{sma}(D_1, 14)$
23 $\min(\Delta C, 5)$	$\text{sma}(D_1, 7)$
24 $\text{sd}(H, 5) - \text{lag}(D, 7)$	$\text{sma}(D_2, 3)$
25 $\text{sma}(\Delta L, 2)$	$\text{sma}(D_3, 3)$

Table IV: Kernel method performance comparison for different feature subsets on 3 different months.

Method and Features	Month-ahead MAPE %				Day-ahead MAPE %			
	Jan. 1999	Dec. 1998	Nov. 1998	Avg.	Jan. 1999	Dec. 1998	Nov. 1998	Avg.
Last Year's Data	2.29	4.79	3.22	3.43	2.29	4.79	3.22	3.43
ARIMA	2.08	4.97	3.45	3.50	2.60	2.55	2.71	2.62
ETS	1.87	4.66	3.47	3.33	2.11	2.48	2.10	2.23
Linear SVM with $H_i(\forall i \in \{k, \dots, k-6\})$	2.32	3.84	1.82	2.66	1.62	2.39	1.99	2.00
Polynomial SVM with $H_i(\forall i \in \{k, \dots, k-6\})$	2.22	3.50	1.82	2.52	1.72	2.39	1.99	2.03
Radial SVM with $H_i(\forall i \in \{k, \dots, k-6\})$	1.96	2.87	1.75	2.19	1.68	2.19	1.81	1.89
Polynomial KRLS with $H_i(\forall i \in \{k, \dots, k-6\})$	3.93	4.71	3.46	4.03	3.91	4.62	3.38	3.97
Radial KRLS with $H_i(\forall i \in \{k, \dots, k-6\})$	1.67	3.06	1.76	2.16	1.61	2.31	1.85	1.92
Using radial KRLS with feature subsets								
$H_i(\forall i \in \{k, \dots, k-6\}) + \text{Temp.}$	3.59	3.05	2.06	2.90	2.25	2.52	1.86	2.21
$H_i(\forall i \in \{k, \dots, k-6\})$	1.67	3.06	1.76	2.16	1.61	2.31	1.85	1.92
D_k^1, D_k^2, D_k^3, S_k	1.88	3.25	1.70	2.27	1.62	2.05	1.84	1.84
$H_k, \Delta H_k, \Delta D_k^1, \Delta D_k^2, \Delta D_k^3, \Delta S_k$	1.64	3.49	1.96	2.36	1.62	2.08	1.93	1.88
$H_k, \Delta H_k, \Delta D_i^1, \Delta D_i^2, \Delta D_i^3, \Delta S_i(\forall i \in \{k-1, \dots, k-6\})$	1.55	3.98	2.56	2.70	1.25	2.61	2.25	2.04
HLC grammar - best of each month	-	-	-	-	1.15	1.73	1.39	1.48
HLC grammar - average of each month	-	-	-	-	1.34	1.89	1.56	1.60
HLC grammar - worst of each month	-	-	-	-	1.62	2.03	1.68	1.68
Wavelet grammar - best of each month	1.42	2.45	1.35	1.84	1.61	1.93	1.66	1.81
Wavelet grammar - average of each month	1.82	2.89	1.54	2.08	1.77	2.31	1.79	1.96
Wavelet grammar - worst of each month	2.42	3.32	1.76	2.31	1.90	2.89	1.98	2.26

many others are not so apparent to human experts. We defer the interpretation of the features in this paper and make our code and results of individual GE trials available at <http://www.ee.usyd.edu.au/cel/ICMLA2013> to facilitate further research as suggested in our conclusion or by any other means.

V. CONCLUSION

In this paper, GE was used to combine the generation and selection of seemingly unconventional input features for electricity load prediction, compactly represented using CFGs. It was found empirically that the approach can improve the 3-month average MAPE for a KRLS based predictor from 1.84% to 1.48% for day-ahead predictions and from 2.16% to 1.84% for month-ahead predictions. Although the EUNITE dataset was used for empirical evaluation, the technique is general and is applicable to many other time-series applications by defining appropriate CFGs based on domain knowledge.

Previous electricity load prediction research has mostly focused on improving different ML algorithms and utilized similar features. This paper described a new approach to automatically generate better features which is independent of the ML algorithm. The approach can be easily applied to other ML architectures as well. By comparing the results to previous work on the dataset [21], we see that even without using any sophisticated ML architectures encouraging results can still be obtained by better formalizing the solution hypothesis using better features. Future research will utilize ensemble FS techniques to ensure that the selected feature subsets are robust for non-stationary time-series and will aid

in minimising the gap between the best and worst performing feature subsets in Table V.

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