Sustainable supply chain management of electric grid power consumption load for smart cities based on second-order exponential smoothing algorithm

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Abstract: - Electric grid power consumption load is one of the fundamental areas that need to be faced to provide a sustainable and green ecosystem in smart cities. Consumption load as well as supply and availability of electricity to suppliers and customers is a major issue to be faced to have a balanced smart city power grid infrastructure. Balancing in this case is assumed as a well-designed supply chain management system to be applied in the Smart City (SC) of Athens, Greece. Core of such a system is the knowledge of electric power consumption load per weekly basis of a year, that is the granularity of the proposed system is one week of the system's operation. In this paper, focus is given on the electric load forecast component of an Energy Management System (EMS) such as the Independent Power Transmission Operator (ITPO) of Greece. Concretely, stochastic data of electric energy consumption load are used to predict the demand or offering of electric power in the future. This is achieved by incorporating a machine learning second-order exponential smoothing algorithm. Such an algorithm is able to speculate near or far in the future power consumption load thus providing a promising parameter to predict smart city needs for electric power in the future. Adopted system is evaluated by the evaluation metric of Normalized Root Mean Square Error (NRMSE), which assures that the system can be used for future predictions of electric power consumption load in smart cities.

Key-Words: sustainable management, supply chain, electric grid, exponential smoothing, smart cities

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1 Introduction

Sustainable and green energy is an area of great importance in smart cities in modern societies around the globe, [1]. Electric energy is one area of such high importance that needs to be treated rationally to become environmentally friendly, [2]. Electric grid is used to transfer electric energy in every place of a smart city to provide advanced wellbeing to citizens of the city, [3]. However, electric power has a disadvantage, that it cannot be stored in huge quantities, [4]. For this purpose, it is fundamental that the city, such as the Smart City (SC) of Athens in Greece, should produce that amount of electric energy that covers its needs without great variance in the produced energy, [5]. Specifically, production should be confronted between two thresholds, that is production of less electric power and production of more electric power than that the population of the city can consume, [6]. Less production leads to buying electric power quantity required from electric energy suppliers, while high production of electric energy leads to selling surplus to potential electric power customers, [7]. Although it is important to have exactly the amount of electric power needed it is rare this balance holds, [8]. Concretely, it is about a supply chain management system, which should be at any time ready to balance surplus or deficit of electric power incorporated by the smart city electric demand infrastructure, [9]. Intuitively, an Energy Management System (EMS) is a system with certain computer applications, automation and control for monitoring. Controlling, scheduling and analysis of the energy power system operation at all levels (production, grid, demand), [10]. Concretely, an EMS comprises a variety of applications and automation technologies, falling in the following basic categories: (1) power system simulator, (2) operation training, (3) state estimation and system monitoring, (4) risk and contingency analysis, (5) load forecast, (6) real time voltage control and grid operation, (7) load shedding, (8) economic dispatch and automatic generation control, and (9) Data analysis.

In this paper we focus on the green and sustainable supply chain management technology of electric energy produced and consumed by the smart city of Athens, Greece. Proposed research effort would not be feasible to operate without the proliferation of Internet of Things (IoT) and artificial intelligence technologies, which provide a safe and sound framework where upcoming technologies can be invented, analyzed and applied in the wider area of a SC. Specifically, we are interested in the electric load forecast component of an EMS such as in the Independent Power Transmission Operator (ITPO) of Greece, [11]. Concretely, special focus is given on the ability to predict the electric energy produced by the city in a granularity of a weekly basis during one year. Such a knowledge would provide us the advantage of when to proactively trigger suppliers or customers of electric power to balance the smart city electric energy. Specifically, we use stochastic historic data from the previous year and apply second-order exponential smoothing machine learning algorithms to speculate future values of electric power required by the city, [12]. To achieve these certain parameters are required, such as the number of the past weekly used values, the prediction time sliding window as well as the time distance in the future we would like to make a prediction. Actually, the adopted machine learning model provides us the opportunity to choose several future values to make a desired prediction. Our model is evaluated with the Normalized Root Mean Square Error (NRMSE) evaluation metric, where results indicate that the adopted approach could be incorporated in actual cases of electric power consuming prediction in the next few years.

Proposed approach focuses on the significance of the current research effort, which can be described in the following list:

- Electric load forecast component applied in the SC of Athens, Greece.
- Online and in real time prediction of electric energy consumed by the city.
- Granularity of the system is defined to be one week, which results in a more robust environment compared with granularities of less time quantities.
- Proposed algorithm is lightweight thus less complex compared with Neural Networks approaches incorporated by other studies in the literature.
- Data used in the proposed research are real and provided by the ITPO of Greece.

The rest of the paper is structured as follows. In Section 2 related work is provided. Section 3 describes the proposed machine learning prediction system algorithm. Section 4 presents the evaluation metric used to assess the efficiency of the proposed machine learning second-order exponential smoothing algorithm. Section 5 analyzes adopted system parameters. In Section 6 certain experiments are based on real data. In addition, results are presented based on the adopted system parameters and the proposed machine learning algorithm. Section 7 performs detailed discussion of the results observed to understand the behavior of the proposed algorithm and its application in the smart city of Athens, Greece. Finally, Section 8 concludes the paper presenting the main aspects of the proposed machine learning algorithm as well as proposes specific research parameters eligible to be performed by certain future work.

2 Related Work

Contemporary research in the area of electric power grid consumption load focuses on efficient prediction schemas, which are able to predict electric energy load in smart cities. Research approaches are sorted based on the parameters of the energy management functions they provide. Concretely, certain groups of research efforts emerged based on prediction spatial scope, granularity and time horizon values incorporated.

2.1 Spatial Scope

According to spatial scope (i.e., the grid area covered) systems are divided in efforts, which cover the whole area of a SC and systems which cover a limited area of the city.

2.1.1 Whole Area of a Smart City

Specifically, a scheduling framework using dynamic optimal electric power flow of electric energy consumption load for battery energy storage systems is proposed, which focuses on mitigating the predicted limits of renewable electric power generation for the smart city infrastructure, [13]. An energy management system, which is designed incorporating fuzzy logic control for relaxing the electric grid power profile of a residential electro-thermal microgrid is proposed for predicting electric consumption load in smart cities, [14]. Such a system aims to design an energy management model to reduce the impact of grid power in cases of overloading.

2.1.2 Limited Area of a Smart City

A hybrid robust system, which considers outliers on real time for electric consumption load series prediction is introduced in, [15]. Specifically, electric consumption load prediction is treated as an important operation of electric power grids, where cost reduction in the production of power is of increased managerial significance. A multi-model fusion short-term electric energy consumption load forecasting system, which is based on random forest feature selection to input a hybrid neural network exploiting sliding window technique, proposed in the literature, [16]. Such a system is able to distinguish the non-linear relationship between various input features.

2.2 Granularity

Research efforts in this category are divided according to the granularity of the designed system (i.e., the single time unit), which might be a single hour, a week or a month ahead of electric load forecast component operation.

2.2.1 Single Hour Ahead Operation

An electric consumption load prediction based on artificial intelligence deep learning model is used to optimize power grid behavior in smart cities, [17]. Proposed system is enhanced by the execution of a heuristic algorithm able to balance electric load in an occupied smart grid. Specifically, the system supports decision making of a smart electric power grid incorporating a feature selection algorithm to mitigate the curse of dimensionality of the input parameters. Adopted system was tested on hourly load data and proved to have an effective accuracy. An improved Long Short-Term Memory (LSTM) spatial-temporal forecasting method is proposed in the literature, which covers electric power grid consumption load needs based on effective Internet of Things (IoT) analysis, [18]. Such a system is implemented based on an efficient machine learning model and compared with other intelligent algorithms in different electric power energy datasets with regards to prediction accuracy evaluation metric. Proposed system achieved higher prediction accuracy than the other machine learning algorithms. Electric consumption load prediction scheme under false data injection attacks is able to be faced using an artificial intelligence deep learning model, [19]. Such a system is able to forecast electric load at different time horizons balancing the needs of producers and customers of a smart city. A cyber-secure deep learning model is constructed, which is able to predict effectively electric consumption load in power grids for a sliding time spanning from an hour up to a week of continuous operation.

2.2.2 A Week Ahead Operation

A demand response visualization system, which is applied for electric power consumption load systems is proposed, [20]. Such a system is refers to activities designed to manage and control electric loads in a smart city. Proposed system also provides visualization capabilities to utilize electric power distribution networks to enable efficient network operation. Short-term electric power consumption load forecasting, which is based on gate recurrent unit networks exploiting cloud computing platform flexibility is proposed, [21]. Such a system has an important role in the entire smart grid infrastructure due to its impact on the scheduling and production of electric power units located in smart cities' infrastructures.

2.2.3 A Month Ahead Operation

Electric power system load prediction analysis incorporating computer neural network technology is proposed, which focuses on economic development of electric power stations in smart cities, [22]. Such a system is related to sustainable industrial economic development to balance electric power consumption needs in smart cities. An electric power load prediction model applied to an electric power substation, which incorporates an efficient artificial neural network is analyzed in, [23]. Such a model is able to estimate, with effective prediction accuracy, the electric power of consumption load produced by a power grid substation. Adopted model incorporates a system operator to assure a reliable and optimal behavior.

2.3 Time Horizon

Time horizon parameter is divided with regards to size of available history as well as size of future prediction. According to this definition there are systems, which use massive information of available history and limited future to be prediction sizes as well as systems that use limited information of available history and also limited future prediction sizes.

2.3.1 Massive Information of Available History

A detailed analysis on Cyber-Physical Power System (CPPS) environments for enabling safe as well as sustainable electric power grids for active consumption load is proposed in the literature, [24]. Examined research effort focuses on the stochastic analysis of cyberattacks in the energy sector of a smart city. Such analyses incorporate the heterogeneous nature of the CPPS to evaluate possible emerging vulnerabilities and threats in the smart city energy infrastructure. A multi-step ahead prediction for electric power consumption load incorporating an ensemble machine learning model is proposed in, [25]. Specifically, the model is based on a two-layer robust structure, which enables experiments to be conducted with different prediction horizons in the future to assess its performance.

2.3.2 Limited Information of Available History

Pricing information in smart electric energy grids focusing on a quality-based data valuation paradigm is proposed, which exploits important assets for the optimal operation and planning of electric power consumption load systems, [26]. A smart electric power grid for forecasting electric consumption load in a smart city network is analyzed, [27]. Such a system aims to frame the deployment of a smart grid based on smart technologies assessment towards an efficient electric energy source for smart grid integration. A mean shift densification of certain data sources feeding short-term electric power load prediction for special days within a year is studied, [28]. Such short-term forecasting has a significant role regarding the operation of electric systems and planning maintenance decision support operation processes within a smart city infrastructure.

Current research efforts focus on accurate supply chain prediction of electric consumption load required by smart cities' power grid infrastructure. There are effective artificial intelligence and machine learning models, which are able to support suppliers and customer balance for electric power during a period stemming from one hour up to one week of operation. However, such proposed solutions are computational inefficient, since they use complex forecasting algorithms, thus burdening the whole smart city electric energy infrastructure. In this paper there is an intention to design a computationally lightweight machine learning algorithm to provide a less complex prediction schema for smart cities' operation. Specifically, we propose to use a supply chain second-order exponential smoothing algorithm, which is able to predict electric consumption load required by smart city power grid operation. Such an algorithm is simple to be designed and applied in the existing infrastructure as well as is also able to predict with efficient prediction accuracy the consumption of electric load required on a weekly basis for a smart city's electric energy operational behavior.

Intuitively, proposed research focuses on a prediction spatial scope (i.e., the grid area covered) of the whole area of the SC of Athens, Greece. In addition, granularity of the designed system (i.e., the single time unit) is defined to be one week of operation. Concretely, time horizon follows the limited information size of available history (e.g., five prior weeks), while size of future to be predicted is experimentally defined to be one week ahead.

Prediction spatial scope is defined to be the whole area of the SC of Athens since real data provided by the Independent Power Transmission Operator (ITPO) of Greece, [11], cover the actual needs of electric load consumption for the city of Athens. Concretely, the proposed system algorithm is based on the provided data to exploit electric load consumption of large-scale performance such as the case of the capital city of Athens, Greece. Intuitively, granularity of input data to the proposed system is defined to be a week since less time period would not have practical interest. Actually, provided data are describing hourly electric load consumption for the city of Athens. However, such detailed information would cause latencies and delays in the proposed system algorithm execution, thus it is performed aggregation of the provided data into weekly basis. Subsequently, the time horizon size of available history is defined to be five weeks so as to be one whole month of the system's operation plus the consecutive week of the provided data. This experimental setup provides the algorithm with more robust historic data thus leading to an efficient system behavior. Concretely, the size of the future is defined to be one week because prediction in a more extended time horizon would lead to loss of precise results, which might result in failure of the system algorithm to provide effective predictions.

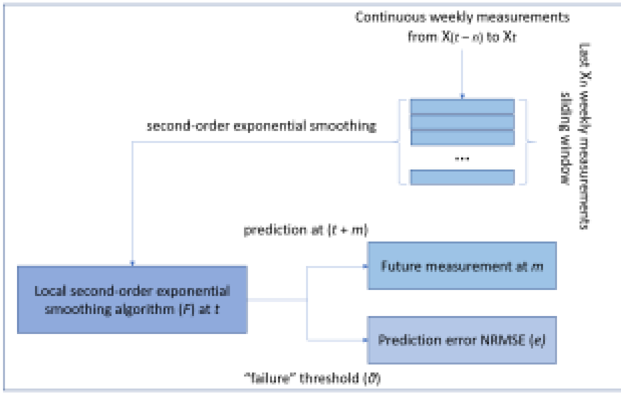

Fig. 1. Visualization of the proposed second-order exponential smoothing algorithm.

3 System Algorithm

Proposed system algorithm is based on the second-order exponential smoothing for the current research effort, which exploits stochastic historical electric data values to predict the next electric consumption load value in the future horizon of a weekly smart city operation, [12]. Such a system is based on the input of continuous weekly electric consumption load measurements the model from $t - n$ up to t. Specifically, $t - n$ is a period of electric values in the past from where the algorithm takes input, while electric measurement value of t is the current electric consumption measurement. Concretely, a sliding window, which contains the last n values is used to input such values to the algorithm. Since the considered values are constrained by the length of n the algorithm is characterized as local, thus in a certain instant it is only processing the n input values. Subsequently, the local second-order exponential smoothing algorithm function, F, performs at time instant t a prediction of the next electric consumption value. However, prediction at time instant t is possible to be done in a time horizon of m weekly measurement steps in the future, thus prediction can be performed in a weekly horizon of $t + m$ electric values. Intuitively, the proposed algorithm should be evaluated with regards to the quality of its prediction based on a threshold ϑ, which is a threshold used to assess the value of the Normalized Root Mean Square Error (NRMSE), e, observed by the algorithm. A predicted electric consumption value is considered as successful if it is less or equal to ϑ, in the opposite case the value is considered as a failure of the adopted algorithm. A visualization of the proposed second-order exponential smoothing algorithm is presented in Fig. 1.

Technically second-order exponential smoothing algorithm, as customized for current research effort, is input by continuous weekly electric values, where the examined actual value is denoted with x_t, which beginning at time instant $t = 0$ [12]. Concretely, it is used in the notation s_t to represent the smoothed weekly electric consumption value for time t. Subsequently, notation b_t is used to characterize the optimal estimate of the algorithm's trend at time t. Intuitively, at this stage it is presented as the output of the second-order exponential smoothing algorithm, which is denoted as F_{t+m}, which is an estimate of the value x_{t+m} at time instance $m > 0$ according to the historical weekly electric values from the sliding window formed between the past time instances from n up to time t. F_{t+m} is defined by the following equation:

$$F_{t+m} = s_t + m \cdot b_t \quad (1)$$

Concretely, given certain input to the machine learning system algorithm specific output is expected to observe a computed electric power weekly consumption load prediction. Second-order exponential smoothing algorithm is presented in Table 1.

4 Evaluation Metric

Assessing the efficiency of an algorithm implies the existence of an evaluation metric. In case of the proposed second-order exponential smoothing algorithm it is adopted the Normalized Root Mean Square Error (NRMSE), e, which takes values within the interval, $e \in [0, 1]$. Concretely, e is defined in the following equation:

$$e = \frac{\sqrt{F_{t+m} - x}}{\bar{\bar{x}}} \quad (2)$$

Where, F_{t+m}, are the dependent predicted electric consumption load values, x, are the actual values, and $\bar{\bar{x}}$, is the average of the actual values of the dependent variable. A low value of e means an efficient exponential smoothing algorithm, while a high value of e means a weak system algorithm. A threshold of $e < 0.5$ indicates that the adopted algorithm has an acceptable prediction behavior, while a value of $e \geq 0.5$ indicates that the mean of the dependent variable distribution cannot be predicted, which means that the algorithm is very weak [29].

Table 1. Second-order exponential smoothing algorithm.

Second-order exponential smoothing algorithm
Input: x_0, x_1
Output: F_{t+m}
Begin
$s_0 \leftarrow x_0$
$b_0 \leftarrow x_1 - x_0$
For $(t > 0)$ **Do**
$s_t \leftarrow a x_t + (1-a)(s_{t-1} + b_{t-1})$ // Where $a (0 \leq a \leq 1)$,
// data smoothing factor
$b_t \leftarrow \beta(s_t - s_{t-1}) + (1-\beta) b_{t-1}$ // Where $\beta (0 \leq \beta \leq 1)$,
//trend smoothing factor
End For
$F_{t+m} = s_t + m \cdot b_t$ // To predict beyond x_t
Return (F_{t+m})
End

Table 2. Adopted system parameters.

Parameter	Value
x: Electric load value (Megawatt hour)	[24.29, 78.89]
n: Sliding window size (Week)	[1, 52]
m: Future prediction horizon (Week)	[1, 5]
e: NRMSE evaluation metric (Net number)	[0, 1]
ϑ: NRMSE threshold value (Net number)	0.5

5 System Parameters

Proposed system was tested on real data, which were provided by the Independent Power Transmission Operator (ITPO) of Greece, [11]. Specifically, input data feed the proposed algorithm are numerical values measured in Megawatt hour. Such electric load is used by the smart city of Athens, Greece supply chain infrastructure to provide the adequate electric consumption energy to balance demand and supply between its citizens' needs as well as the interested suppliers and customers. Electric values are aggregated to weekly consumption by ITPO to provide a stable electric flow in the power grid of the city. Megawatt hour in the city for a weekly basis is within the following numeric interval $x \in [24.292, 78.893]$. Sliding window size required by the proposed algorithm to operate is within the following interval, $n \in [1, 52]$, since working weeks of a year are approximately 52 weeks. Future prediction horizon of a forecasted electric consumption load value is defined to be within the interval, $m \in [1, 5]$. Normalized Root Mean Square Error (NRMSE), e, is defined to have the following threshold value $\vartheta = 0.5$, which is net number. Adopted system parameters are presented in Table 2.

Table 3. Experimental benchmark dataset values in Megawatt hour per week granularity.

Week	Value	Week	Value	Week	Value	Week	Value
1	24.29	14	63.75	27	73.56	40	61.69
2	67.28	15	71.31	28	71.89	41	58.83
3	74.94	16	76.67	29	75.08	42	55.38
4	77.82	17	77.36	30	72.05	43	51.27
5	65.64	18	77.85	31	73.09	44	48.59
6	58.09	19	65.04	32	74.44	45	25.49
7	57.86	20	70.62	33	76.78	46	27.37
8	65.68	21	62.58	34	78.12	47	66.88
9	56.18	22	66.61	35	72.21	48	61.91
10	58.97	23	64.24	36	75.56	49	52.98
11	67.32	24	70.06	37	67.52	50	49.91
12	69.52	25	78.89	38	68.86	51	34.16
13	72.13	26	75.22	39	65.37	52	25.59

6 Experiments and Results

We experimented with the proposed second-order exponential smoothing algorithm based on the adopted evaluation metric NRMSE, e, and defined system parameters. Experimental smart city is the capital city of Greece, which is Athens. Data used for the experiments are denoting electric energy load consumption per week of electric power grid operation by the smart city of Athens as provided by the system parameter, x. Experiments are performed to evaluate the effectiveness of the proposed algorithm with further scope to adopt such a system in real life scenarios, which may emerge and need treatment by the load forecast component of the ITPO. Such a benchmark dataset is consisting of real data for the year 2021, which are available online by the ITPO [11]. Concretely, experimental data are processed in a granularity of a week operation, which input the load forecast component of the SC of Athens, Greece ITPO. Detailed values of the available real data per week for a total period of 52 weeks, which cover the period of a working year are presented in Table 3.

Proposed machine learning algorithm is implemented in Python release version 3.9.10, while experiments were performed on a HP ProBook 455R G6 computer with 8.00 GB memory. We performed 1000 experimental iterations invoking adopted second-order exponential smoothing, where the observed results were visualized. Specifically, experiments focused on defining the optimal value of defined evaluation metric NRMSE, e, for sliding window size, n, while simultaneously fine tuning the optimum value for future prediction horizon, m, according to certain error threshold, ϑ. Experimental results are presented in Fig. 2.

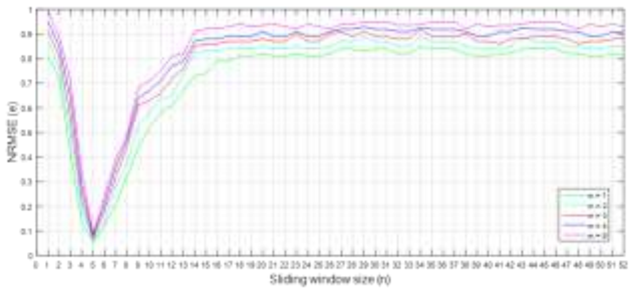

Fig. 2. Visualization of the NRMSE, e, values for certain sliding window size, n, values and adopted future prediction horizon, m, values.

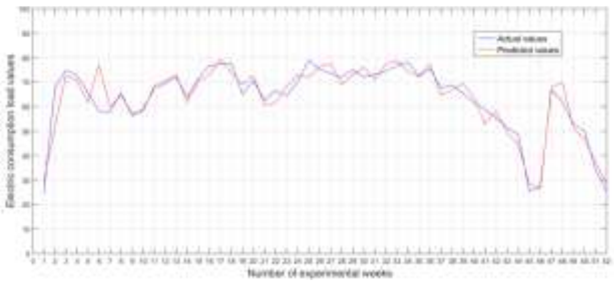

Fig. 3. Visualization of actual and predicted values for certain sliding window size, $n = 5$, value and adopted future prediction horizon, $m = 1$, value.

It can be noted that optimal predicted values are observed for sliding window size value, $n = 5$, and future prediction horizon, $m = 1$. Concretely, NRMSE observed values are within range $e \in [0.04, 0.08]$. Predicted observations along with actual data values, for such parameter settings, are presented in Fig. 3.

7 Discussion

Proposed second-order exponential smoothing algorithm is a lightweight solution to the electric load prediction problem since it can provide relatively accurate predictions online and in real time. Concretely, the adopted algorithm is able to quantify in its analytical formulae the quantities of input data and their trend towards an output prediction. However, an extension of this algorithm would take into consideration the quantity of seasonal change smoothing factor, which might affect positively and improve the effectiveness of the algorithm. This is an open issue the authors have scheduled to study in the future work.

Intuitively, the proposed algorithm incorporates several parameters, which should be explained in more depth to understand how the algorithm infers a prediction in the future. Input values are the sequential values of the electric load data stream, which actually has a vital impact on the overall performance of the adopted algorithm. Concretely, an electric energy value data stream may be accessed as a data signal and as that a safe and sound input flow is more possible to lead to valid output predictions than that in case of a random like data stream. Subsequently, data smoothing factor, α, is better understood as a factor which unlocks the potentiality of arithmetic electric load data values, which can then be exploited better by the algorithm. Intuitively, trend smoothing factor, β, can contribute in making the algorithm to understand the current positive or negative arithmetic trend the manipulated data have while time is passing and prediction is required as soon as possible. However, there is no golden ratio or default known values for the computed α and β values since they both depend on the quality and inherent noise of the input electric load data stream values. Actually, this is the existing issue in machine learning since there is nothing to be taken for granted. Instead, every single parameter of the selected algorithm should undergo a certain number of iterations to converge in an acceptable efficiency level where the parameters are considered stable and able to provide valid predictions.

A challenging issue the proposed model has to deal with in real-life environments is the balance of the SC's electricity grid. Such a problem is crucial to maintain an operational electricity grid in SCs. Specifically, the amount of electricity load input to the electricity grid should in any case be equal to the amount of electric load consumed. If this is not feasible there is a high possibility of a black-out in the city's infrastructure. Subsequently, the contemporary increase of renewable electric production that can significantly vary depending on the weather conditions has a more complicated impact to the existing electric balance issue. In addition, existing power plants should be able to compensate for these constant fluctuations, since there is not the feasibility to store electricity in vast quantities over a long period of time [30]. Since the proposed algorithm is part of the load forecast component of the adopted EMS for the SC of Athens, Greece it is able to predict the future electric consumption values required by the SC. Such knowledge enhances the EMS to achieve electricity balance proactively, that is before this situation will actually happen. Intuitively, this possible proactiveness is a strategic managerial tool, which is feasible due to the adopted algorithm.

Concretely, results of the proposed machine algorithm are promising to provide efficient supply chain sustainable management services by the smart city of Athens, Greece. Specifically, experiments performed for a period of a year containing electric energy consumption load for 52 weeks of system operation provide a robust power grid infrastructure. As it can be observed by the obtained NRMSE, e, values, proposed system algorithm is able to predict future electric power consumption load for the smart city for certain values of sliding window size, n, per certain values of future prediction horizon, m. NRMSE, e, efficiency increases, thus values of NRMSE, e, are decreased since these are error values and the smaller they are the better the adopted second-order exponential smoothing algorithm performance is achieved.

We can observe that NRMSE, e, decreases as sliding window size n, increases from one week of operation up to five weeks of power grid operation for all values of future prediction horizon m. However, we can observe there is a global minimum at the sliding window size, n, for value of $n = 5$, while increased values of n lead to higher values of e, thus performance of the system is decreasing. This is explained since the system learns from incremental experience for $n \in [1, 5]$. When $n = 5$ algorithm has learned the behavior of electric energy consumption load in the smart city for a month and a new week, i.e., the 5th week of operation. Since with $n = 5$ the system is more robust due to the completion of a whole circle of temporal training plus a new unseen instance, which is the first week of the next month, is now ready to perform its first extrapolation attempt with values of $m \in [1, 5]$.

It can be observed that the $n = 5$ proposed algorithm can predict well with almost all future prediction horizons m, values. However, if we need more insight into future need for electric power consumption by the smart city we would feed the algorithm with more increasing values of sliding window size, thus $n \in [6, 52]$. It is obvious that as n increases external noise is entered to the algorithm, which has a negative impact to its e. So, the more the input n values the worse e values observed. Concretely, the future horizon of prediction is going worse for all values of m. However, it is interesting to observe that in this condition lower values of m achieve lower values of e, thus overall performance for $m = 1$ is marginally better for other values, i.e., $m \in [2, 5]$. By this point of view future work in this research area should focus on computationally lightweight machine learning algorithms, as the proposed second-order exponential smoothing algorithm, which should exploit the dynamics of such prediction property, (i.e., better future prediction outcomes for $m = 1$), of the examined electric power weekly grid supply.

Intuitively, in Fig. 3 it can be observed the actual input values to the model and the output predicted values, which are provided to the load forecast component of the examined system. Specifically, in Fig. 3 it is presented the actual and predicted electric consumption load values for a period of the year 2021 aggregated per working week, thus a total of 52 weeks of a year. Note that the output predicted values' plotted line marginally well aligned with the actual input values' plotted line, respectively. Subsequently, it can be inferred that the NRMSE error range is within, $e \in [0.04, 0.08]$, which indicates that the proposed algorithm is efficiently accurate and can be proposed for adoption to the SC of Athens, Greece ITPO. Such a concrete framework can face daily emerging situations, which may occur in the electric energy grid of the city in the next years of online and in real time operation.

8 Conclusions and Future Work

A sustainable supply chain technology is analyzed in this paper, which incorporates a second-order exponential smoothing machine learning algorithm to balance electric power dynamics between suppliers and customers of the smart city of Athens, Greece. Such an algorithm is part of the load forecast component of the SC's EMS, which is responsible to maintain electricity balance in the city. This is highly important since an unbalanced electric grid is prone to an unexpected black-out. Electric power consumption load is treated as a machine learning data source, which inputs the proposed algorithm to provide a green ecosystem based on existing electric power grid infrastructure. Balancing the needs or surplus of electric energy is feasible due to continuous operation of the adopted machine learning algorithm. Core of the system algorithm is the knowledge of electric power consumption load per weekly basis of a year. Concretely, stochastic data of electric energy consumption load are used to predict the demand or offering of electric power in the future. Such a prediction is feasible by using the proposed second-order exponential smoothing algorithm, aiming to speculate near or far in the future power consumption load thus providing a promising parameter to predict smart city needs for electric power consumption load in the future. Main parameters of the algorithm are data, a, and trend, β, smoothing factors, which exploit the nature of the input data as well as their positive or negative trend.

Adopted system is evaluated by the evaluation metric of Normalized Root Mean Square Error (NRMSE), which assures that the system can be used for future predictions of electric power consumption load in smart cities. Subsequently, predicted electric consumption load values observed are marginally well aligned to the input actual values, which is an indicator of the proposed system's efficiency. Future work should focus on exploiting the quantity of the seasonal change smoothing factor, which might affect the effectiveness of the proposed model. However, there is no golden ratio or default known values for the computed α and β values since they both depend on the quality and inherent noise of the input electric load data stream values. Actually, this is the existing issue in machine learning since there is nothing to be taken for granted. Instead, every single parameter of the selected algorithm should undergo a certain number of iterations to converge in an acceptable efficiency level where the parameters are considered stable and able to provide valid predictions. Intuitively, since the proposed system is lightweight it should be compared with other approaches in the literature to compare its effectiveness with more complex algorithms in consecutive future work. Subsequently, such comparison should be done with regards to certain experimental parameters that are the variety of prediction spatial scope, granularity and time horizon values as defined in the current research effort. Focus will be on the principle of equal treatment for all of the compared electric grid consumption load solutions applied in a green and sustainable SC infrastructure.

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