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Advanced Application of Linear Programming for Optimal Solutions for the Meteorological

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Abstract – Meteorological data play a particularly important role in hydrologic research because the climate and weather of an area exert a profound influence on most hydrologic processes. Meanwhile, hydrological data are critical for performing a range of purposes, including water resources assessment, impacts of climate change, flood forecasting and warning. It can be said that the prevention of disasters caused by floods and droughts would be impossible without rational forecasting technology based on an understanding of the rainfall-runoff phenomenon and statistical analysis of past hydrological data, which cannot be achieved without meteo-hydrological observations. The lack of adequate meteo-hydrological data affects the ability to model, predict and plan for catastrophic events such as floods and droughts which have obvious negative impacts on public health and socio-economic aspects. The accurate estimation of the spatial distribution of meteo-hydrological parameters requires a dense network of instruments, which entails large installation and operational costs. It is thus necessary to optimize the number and location of meteo-hydrological stations which gives greater accuracy of meteo-hydrological data estimation with minimum cost.

Keyword – Meteorology, Hydrological, Technology

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INTRODUCTION

Linear programming was developed during World War II, when a system with which to maximize the efficiency of resources was of utmost importance. New war-related projects demanded attention and spread resources thin. "Programming" was a military term that referred to activities such as planning schedules efficiently or deploying men optimally. George Dantzig, a member of the U.S. Air Force, developed the Simplex method of optimization in 1947 in order to provide an efficient algorithm for solving programming problems that had linear structures. Since then, experts from a variety of fields, especially mathematics and economics, have developed the theory behind "linear programming" and explored its applications.

We can reduce the structure that characterizes linear programming problems (perhaps after several manipulations) into the following form

$$\begin{array}{lccccccccc}
\text{Minimize} & c_1x_1 & + & c_2x_2 & + & \cdots & + & c_nx_n & = & z \\
\text{Subject to} & a_{11}x_1 & + & a_{12}x_2 & + & \cdots & + & a_{1n}x_n & = & b_1 \\
 & a_{21}x_1 & + & a_{22}x_2 & + & \cdots & + & a_{2n}x_n & = & b_2 \\
 & \vdots & & \vdots & & & & \vdots & \vdots & \vdots \\
 & a_{m1}x_1 & + & a_{m2}x_2 & + & \cdots & + & a_{mn}x_n & = & b_m \\
 & x_1, & & x_2, & & \ldots, & & x_n & \geq & 0.
\end{array}$$

In linear programming z, the expression being optimized, is called the objective function. The variables x1, x2 . . . xn are called decision variables, and their values are subject to m + 1 constraints (every line ending with a bi , plus the nonnegativity constraint). A set of x1, x2 . . . xn satisfying all the constraints is called a feasible point and the set of all such points is called the feasible region. The solution of the linear program must be a point (x1, x2, . . . , xn) in the feasible region, or else not all the constraints would be satisfied.

$$
\begin{array}{lrcrcl}
\text{Minimize} & 4x_1 & + & x_2 & = & z \\
\text{Subject to} & 3x_1 & + & x_2 & \geq & 10 \\
 & x_1 & + & x_2 & \geq & 5 \\
 & x_1 & & & \geq & 3 \\
 & & & x_1, \; x_2 & \geq & 0.
\end{array}
$$

We plotted the system of inequalities as the shaded region in Figure 1. Since all of the constraints are "greater than or equal to" constraints, the shaded region above all three lines is the feasible region. The solution to this linear program must lie within the shaded region. Recall that the solution is a point (x1, x2) such that the value of z is the smallest it can be, while still lying in the feasible region. Since z = 4x1 + x2, plotting the line x1 = (z − x2)/4 for various values of z results in isocost lines, which have the same slope. Along these lines, the value of z is constant. In Figure 1, the dotted lines represent isocost lines for different values of z. Since isocost lines are parallel to each other, the thick dotted isocost line for which z = 14 is clearly the line that intersects the feasible region at the smallest possible value for z. Therefore, z = 14 is the smallest possible value of z given the constraints. This value occurs at the intersection of the lines x1 = 3 and x1 + x2 = 5, where x1 = 3 and x2 = 2.

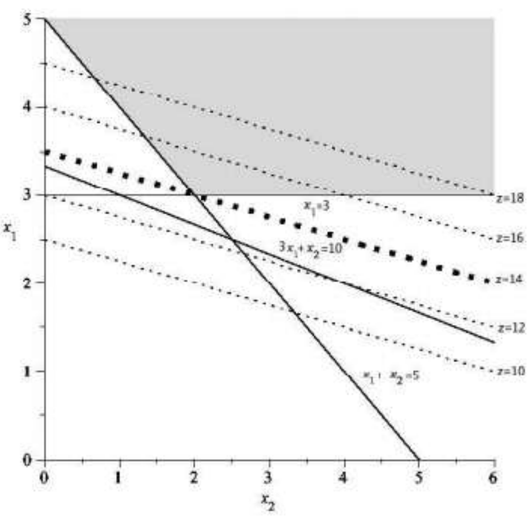


Figure 1: The shaded region above all three solid lines is the feasible region (one of the constraints does not contribute to defining the feasible region). The dotted lines are isocost lines. The thick isocost line that passes through the intersection of the two defining constraints represents the minimum possible value of z = 14 while still passing through the feasible region.

ASSUMPTIONS

Linear programs, it is important to review some theory. For instance, several assumptions are implicit in linear programing problems. These assumptions are:

1. **Proportionality** The contribution of any variable to the objective function or constraints is proportional to that variable. This implies no dis5 counts or economies to scale. For example, the value of 8x1 is twice the value of 4x1, no more or less.

2. **Additivity The contribution** of any variable to the objective function or constraints is independent of the values of the other variables.

3. **Divisibility Decision** variables can be fractions. However, by using a special technique called integer programming, we can bypass this condition. Unfortunately, integer programming is beyond the scope of this paper.

4. **Certainty This assumption is** also called the deterministic assumption. This means that all parameters (all coefficients in the objective function and the constraints) are known with certainty. Realistically, however, coefficients and parameters are often the result of guess-work and approximation.

BENEFITS DERIVED FROM APPLICATIONS

Many benefits result from the application of meteorological services to agriculture. The productivity of a region or of a particular enterprise may be increased by the reduction of many kinds of loss resulting from unfavourable climate and weather, and also by the more rational use of labour and equipment. Greater economy of effort is achieved on the farm, largely by the reduction of activities that have little value or are potentially harmful. All of these increase the competitiveness of production, reduce risk and help to reduce the cost of the final products.

In the developed world, a significant portion of recent work in agricultural meteorology has shifted from increasing yields to reducing the environmental impact of agricultural fertilizer and pesticide use and combating pests and diseases. In the developing world, much of the focus remains on increasing agricultural production but there is also an emphasis on sustainable agricultural production and reducing the impact the pest and diseases (i.e. desert locusts). The following are brief examples of economic benefits of agrometeorological applications from

Rijks and Baradas (2000). In Sudan, precise calculations of water requirements for the main irrigated crops (cotton, sorghum, and groundnut) were compared with available irrigation water to allow for more accurate estimates of potential irrigated wheat area. The net result was an additional 8000 ha of wheat grown that added more than US$ 2 million to the national economy at a cost of few thousand dollars for data, analysis, and staff. In the Gambia, groundnuts are stored in the open air and if the dry pods are wetted they are at high risk of developing aflatoxin that can reduce farmer prices for the crop by 60%. By providing forecasts of rainfall to warn farmers via local radio, farmers can cover the crop with plastic sheeting. It is estimated that for each percent of production saved, the benefit is US$ 60,000. In the Sahel, bush fires are common every year but the bush vegetation is needed for cattle and sheep grazing. By using wind, temperature, and humidity observations to indicate speed and direction of the fire, control burning can take place to prevent the fires from spreading. Reducing the burned area on 1% of the grazing land allows 5000 more sheep to graze or an annual value of US$100,000 added to national economy. Rijks (1992) provided a framework for analyzing costs and benefits of agrometeorological applications in plant protection.

OBJECTIVE OF THE STUDY

1. To describe constrained optimization models.

2. To understand the advantages and disadvantages of using optimization models.

METHODS

Previous study on the energy plan of the Dubrovnik region showed that the integration of high share of RES and EV batteries in the electricity system still results in the critical excess of electricity production. These results indicate a demand for a larger capacity of storage facilities or new solutions to gain stability and flexibility of the system, in order to reduce a critical excess of electricity production. Gained results indicate the need for further future work in order to encourage the integration of RES into the power system and maintain its stability and flexibility. One of the solutions will be obtained within this work through the correlation and regression analyses in between RES potentials and electricity demand. Calculations of the linear correlation and regression will provide the results, based on which it can be estimated a complementarity between solar and wind potential and their complementarity with the electricity demand of the Dubrovnik region. The results could help in the future energy planning of the region’s power system and enhance the integration of RES in the electricity production. Further work can be done, based on these results, in order to estimate optimal mix of RES in electricity production according to the electricity demand of the region. Studies [23-26], mentioned earlier in the text, have shown the results of the correlation analyses between the RES potential and electricity production and the electricity demand load on the monthly and the hourly bases. This work will go a step further and will provide the results of the correlation and regression analyses in the 10 minutes time horizon for different sets of selected data. Results of the calculations based on the 10 minute time step data can play a significant role for the possible future open energy market based on the 10 minute time step. Implementation of open energy market could also enhance the integration of RES into the power system, as well as help to reduce critical excess of electricity production.

Measuring and preparing the input data

The data of the parameters used in the analyses, including solar radiation, wind speed, air temperature and electricity demand, are collected for the years 2012, 2013 and 2014 and the calculations are done for the time step of t = 10 min. Data of solar radiation, wind speed and air temperature of the Dubrovnik region are provided by Croatian Meteorological and Hydrological Service for the years 2012, 2013 and 2014 in the 10 minute time horizon. Measured data are gained from the meteorological station Dubrovnik. The device for measuring wind speed was anemometer with a performance of hemisphere and accuracy of ±5% (5-75 m/s), with a range of 0.5-75 m/s. The equipment for measuring solar radiation was CMP21 Pyranometer with the specifications provided in reference, CVF4 Ventilation Unit for global radiation measurements with the specifications provided in and CM121 Shadow Ring for diffuse radiation measurements with the specifications provided in . Air temperature was measured with Campbell-Stokes heliograph and Lambrecht thermograph. Heliograph measures radiations higher than 0.838 J/cm2 per minute and when Sun is three degrees above the horizon. Thermograph measurement uncertainty is around 0.3 degree in the standard 10 degrees Celsius. Electricity demand data of the Dubrovnik region are provided by Elektrojug Dubrovnik – HEP ODS Ltd., the distribution system operator, for the years 2012, 2013 and 2014 in the 15 minute time horizon. Electricity demand data were arranged in the 10 minute time horizon using linear interpolation.

Diagrams in fig. 1 show the distributions of mean monthly values of the selected parameters for each year normalized to their maximum value. A stands for distributions in 2012, B for 2013 and C for the year 2014. It can be concluded from the diagrams that the electricity demand depends on air temperatures. During the summer period, June, July, August and September, electricity demand increases as the temperature increases due to the need of cooling demand. During the winter period, January, February, November and December, electricity demand increases as the temperature decreases due to the need of heating demand.

Wind electricity production could be used to supply most of the electricity demand during the winter period due to the higher values of wind during the summer period due to the high solar radiation.

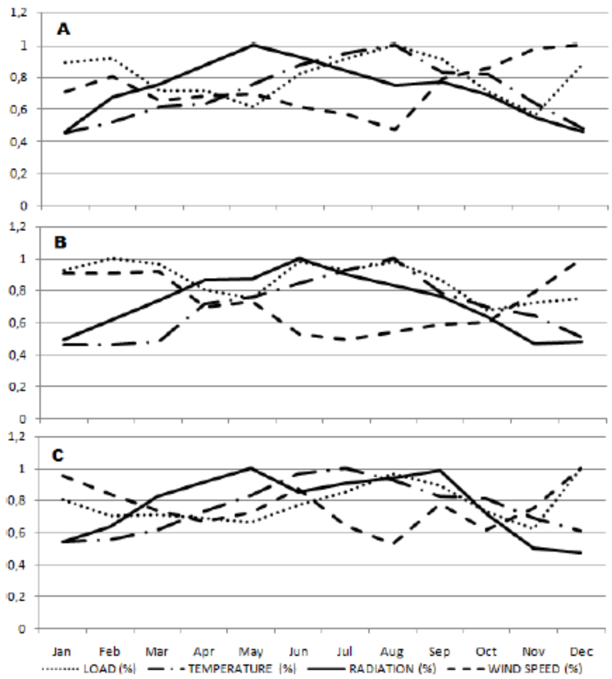


Figure 1. Mean monthly values normalized to their speed. On the other hand, solar elecmaximum value tricity production could be used to supply most of the electricity demand

The problem with collected data of solar radiation, wind speed and temperature was that some of the data are missing. The data are missing mostly from the summer period of July and August. Solar radiation, for example, should reach its maximum during July and August, but because of the lack of data we have maximum during May and June. Results in tab. 1 show maximum and minimum mean monthly values for each of the parameters for every year.

Table 1. Values of the correlation coefficient between the selected variables with data based on the mean monthly values

	Load [kW]	Temperature [°C]	Radiation [Jcm^{-2}]	Wind speed [ms^{-1}]
Max (2012)	48,272.19	27.7	202.05	4.93
Min (2012)	28,460.92	7.43	41.61	2.46
Max (2013)	39,573.39	26.39	201.46	5.40
Min (2013)	24,636.00	9.74	41.75	2.58
Max (2014)	36,268.27	25.33	176.77	5.35
Min (2014)	23,537.71	11.58	31.72	2.69

LINEAR CORRELATION AND REGRESSION

The linear correlation and regression analyses are done for the different selected sets of data in order to establish the relationship between the parameters. First analysis (1) is done for each of the parameters individually to examine a linear relationship between the 10 minute data, t = 10 min, in between the years. Second analysis (2) is done in order to establish a linear relationship in between the parameters for each of the selected years separately based on the mean monthly values. Third set of data (3) were data of all the parameters arranged in 10 minute time step through the year, with the additional analysis which included system time delay between the electricity production and the demand. Electricity demand and air temperature are arranged for the period of t = 10 min and solar radiation and wind speed are taken for the time step of t1 = t + 4 h. Since the meteorological data are different for different parts of the year, for example difference between the data of winter and summer period, the last analyses (4) are done for summer and winter periods. Summer period for each year was determined according to the highest temperature and highest peak electricity demand for three months in a row. Winter period for each year was determined according to the lowest temperature and highest peak electricity demand for three months in a row. The linear correlation and regression analyses are done for the data arranged in 10 minute time step between each of the parameters for two periods of each year separately.

Analyses are based on the model of simple linear regression and correlation providing the results of correlation coefficient, coefficient of determination and linear regression line between selected parameters. Calculations are done in STATISTICA, a comprehensive analytic, research and business intelligence tool used in business, data mining, science and engineering applications . Calculations in STATISTICA, for this study, are based on basic formulas of linear correlation. Flow chart in fig. 2 is presenting a method used in this work. Formula in fig. 2 is presenting a basic formula of linear regression line gained from the calculations of the linear correlation were we have:

$\hat{y}_i$ – dependent variable,

$\hat{x}_i$ – independent variable,

a – constant, the expected value of the dependent variable when the independent variable is zero, and

b – regression coefficient shows the average change in the dependent variable caused by the change of the independent variable.

Dependent variable in other case can also be observed as an independent variable and a and b values will be different for that regression line. The coefficient of determination, r2, is a key output of the regression analysis. It is interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variable. The Pearson product-moment correlation coefficient, r, illustrates a quantitative measure of some type of correlation and dependence, meaning statistical relationship between two or more random variables or observed data values.

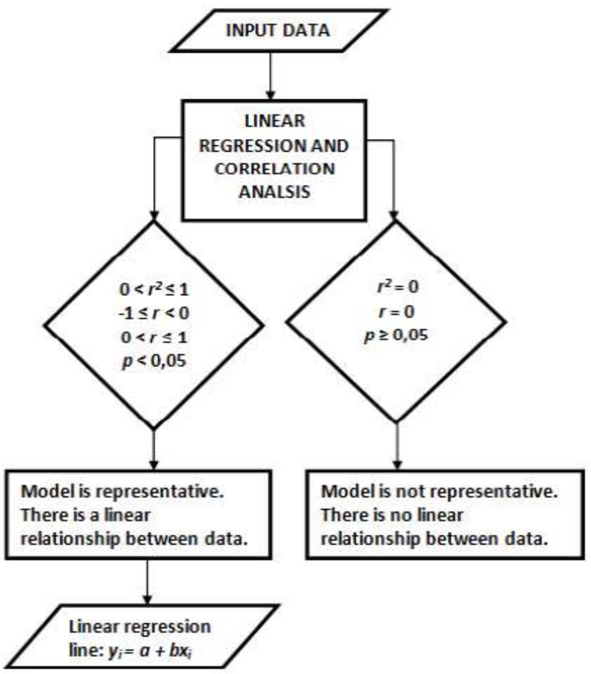
RESULTS AND DISCUSSION

Linear correlation and regression are done for the different sets of data based on the mean monthly values and 10 minute time step as it is explained in sub-section 1.2. The results of the calculations are provided in the following sub-sections.

Calculation results based on the first data set in 10 minutes time step for consecutive three year period

Calculations for the first data set (1) are split in four parts analysing the relationship between each of the parameters individually in between the years 2012, 2013 and 2014. Calculations are done for solar radiation, wind speed, air temperature and electricity demand data based on the 10 minute time step through the whole year. Re-selected parameters in between the years, from which can be determined each of the linear regression line according to the equation given in fig. 2.

Figure 2. Flow chart sults are obtained in tab. 2 with given values of r, r2, a and b for each of the



Variables x and y in the equation of linear regression line can be replaced with electricity demand (En, [kW]), solar radiation, (In, [Jcm−2]), air temperature, (Tn, [°C]), and wind speed, (Vn, [ms−1]), where n stands for the data of the years 2012, 2013 or 2014 and will have the same meaning in other calculations. Value N represents a number of data used in calculations. Results show the value of correlation coefficient r between two selected variables x and y and coefficient of determination r2. Constant a and regression coefficient b in the equation of linear regression line are given for the case if y is the dependent variable or x is dependent variable. Equation of the linear regression line between variables x and y can be pronounced using values of constant a and regression coefficient b. Results of the calculations between the variables show significant relationship, p < 0.05, meaning there is a good probability that the observed relation between variables in the sample is a reliable indicator of the relation between the respective variables in the population. Value of correlation coefficient indicates significant linear correlation between the variables En, In and Tn, which means that their distributions in 10 minute time step slightly vary between consecutive three years period and they can be forecasted using linear regression line. Correlation coefficient for Vn distribution is close to 0 which means that the wind speed is hard to predict and data vary in between the years.

Table 2. Calculation results of the first data set in 10 minutes time step for consecutive three year period Calculation results of the second set of data based on the mean monthly values

x, y	Mean	Std. dev	r(x, y)	r^2	p	N	a, y	b, y	a, x	b, x
Electricity demand										
E_{2012}	38,219.50	10,661.31								
E_{2013}	33,931.98	8,930.11	0.851455	0.724976	0.00	52,560	6,674.044	0.713195	3,726.995	1.016519
E_{2012}	38,219.50	10,661.31								
E_{2014}	28,474.17	7,059.98	0.838916	0.703779	0.00	52,560	7,241.920	0.555535	2,146.973	1.266851
E_{2013}	33,931.98	8,930.11								
E_{2014}	28,474.17	7,059.98	0.791839	0.627009	0.00	52,560	7,232.307	0.626013	5,412.514	1.001591
Solar radiation										
I_{2012}	106.5377	162.3647								
I_{2013}	103.1322	161.0447	0.828616	0.686605	0.00	34,822	15.57103	0.821880	20.38026	0.835408
I_{2012}	106.5377	162.3647								
I_{2014}	97.8802	158.2237	0.817296	0.667972	0.00	34,822	13.02800	0.796451	24.44705	0.838685
I_{2013}	103.1322	161.0447								
I_{2014}	97.8802	158.2237	0.768492	0.590580	0.00	34,822	20.01220	0.755030	26.57099	0.782194
Air temperature										
T_{2012}	17.16265	7.483789								
T_{2013}	17.19362	6.473829	0.872629	0.761481	0.00	48,667	4.23814	0.754865	−0.18167	1.008764
T_{2012}	17.16265	7.483789								
T_{2014}	17.14066	5.622084	0.810729	0.657282	0.00	48,667	6.68778	0.609048	−1.33547	1.079195
T_{2013}	17.19362	6.473829								
T_{2014}	17.14066	5.622084	0.794331	0.630962	0.00	48,667	5.28010	0.689823	1.51554	0.914672
Wind speed										
V_{2012}	3.552737	3.137801								
V_{2013}	3.774814	3.369657	0.103533	0.010719	0.00	47,248	3.379809	0.111183	3.188810	0.096409
V_{2012}	3.552737	3.137801								
V_{2014}	3.746781	3.135703	0.149070	0.022222	0.00	47,248	3.217529	0.148970	2.993831	0.149170
V_{2013}	3.774814	3.369657								
V_{2014}	3.746781	3.135703	0.072837	0.005305	0.00	47,248	3.490923	0.067780	3.481547	0.078272

Analyses of the second set of parameters (2) are done for each year separately to establish linear relationship in between electricity demand, solar radiation, wind speed and air temperature data for each year separately. Data are based on the mean monthly values for each of the parameter and the results are shown in tab. 3. Calculations based on the mean monthly values are done in order to compare the results with results from previous studies.

Results in tab. 3, that are not marked bold, show that there is no linear relationship between the variables since their p > 0.05. Correlation results of E2014 vs. T2014 and E2014 vs. I2014 indicate good relationship between variables and are marked bold. Previous study done for Brazil [26] showed that r = 0.46 in case of E vs. I, while in case of E vs. V was r = 0.29. Good correlation results are provided for Tn vs. In, Tn vs. Vn and Vn vs. In. Study done for Italy [22] compared V vs. I on monthly bases and provided the results of correlation coefficient reaching values lower than −0.8 in several areas and for the nation-wide gained values were between −0.65 and −0.6, while the value of r was even closer to 0 for the daily based data. Linear regression line can be written using the equation of linear regression and the gained results.

Table 3. Calculation results of the second data set based on the mean monthly values for consecutive three year period

x, y	Mean	Std. dv.	$r(x, y)$	r^2	p	N	$a; y$	$b; y$	$a; x$	$b; x$
					2012					
E_{2012}	38,221.26	6,703,026								
T_{2012}	17.67	7,157	0.278244	0.077420	0.381196	12	6.32	0.00	33,616.32	260.61
E_{2012}	38,221.26	6,703,026								
I_{2012}	113.13	57,820	0.323019	0.104341	0.305783	12	6.64	0.00	33,984.69	37.45
E_{2012}	38,221.26	6,703,026								
V_{2012}	3.59	0.980	−0.264313	0.069862	0.406446	12	5.06	−0.00	44,702.76	−1,807.95
T_{2012}	17.67	7,157								
I_{2012}	113.13	57,820	0.794745	0.631620	0.002009	12	−0.32	6.42	6.54	0.10
T_{2012}	17.67	7,157								
V_{2012}	3.59	0.980	−0.834147	0.695801	0.000743	12	5.60	−0.11	39.51	−6.09
I_{2012}	113.13	57,820								
V_{2012}	3.59	0.980	−0.812641	0.660386	0.001315	12	5.14	−0.01	285.03	−47.95
					2013					
E_{2013}	33,945.51	5,087,649								
T_{2013}	17.57	6,024	0.203949	0.041595	0.524908	12	9.37	0.00	30,919.74	172.26
E_{2013}	33,945.51	5,087,649								
I_{2013}	114.51	61,956	0.459679	0.211304	0.132711	12	−75.51	0.01	29,622.99	37.75
E_{2013}	33,945.51	5,087,649								
V_{2013}	3.80	1,068	−0.226821	0.051448	0.478368	12	5.42	−0.00	38,051.79	−1,080.36
T_{2013}	17.57	6,024								
I_{2013}	114.51	61,956	0.903236	0.815835	0.000057	12	−48.67	9.29	7.51	0.09
T_{2013}	17.57	6,024								
V_{2013}	3.80	1,068	−0.862404	0.743740	0.000307	12	6.49	−0.15	36.05	−4.86
I_{2013}	114.51	61,956								
V_{2013}	3.80	1,068	−0.841384	0.707928	0.000602	12	5.46	−0.01	300.00	−48.80
					2014					
E_{2014}	28,452.90	3,654,105								
T_{2014}	17.52	5,100	0.774233	0.599436	0.003117	12	−13.23	0.00	18,736.92	554.70
E_{2014}	28,452.90	3,654,105								
I_{2014}	104.55	55,722	0.637465	0.406361	0.025759	12	−172.04	0.01	24,082.46	41.80
E_{2014}	28,452.90	3,654,105								
V_{2014}	3.74	0.987	−0.477260	0.227777	0.116651	12	7.41	−0.00	35,068.73	−1,767.76
T_{2014}	17.52	5,100								
I_{2014}	104.55	55,722	0.845374	0.714657	0.000534	12	−57.23	9.24	9.43	0.08
T_{2014}	17.52	5,100								
V_{2014}	3.74	0.987	−0.806156	0.649888	0.001541	12	6.47	−0.16	33.11	−4.17
I_{2014}	104.55	55,722								
V_{2014}	3.74	0.987	−0.863273	0.745241	0.000298	12	5.34	−0.02	287.03	−48.76

Calculation results of the third set of data based on 10 minutes time step

The analyses of the third set of data (3) are done for each year separately to establish a linear correlation and regression in between the selected variables based on the 10-minute time horizon. The results are provided in tab. 4. Case A represents the results of the calculations done for the time step, t = 10 min, and case B represents the results for including system time delay, t1 = t + 4 h, for each year separately.

Table 4. Calculation results of the third set of data based on 10 minutes time step

x, y	Mean	Std. dv.	$r(x, y)$	r^2	p	N	$a; y$	$b; y$	$a; x$	$b; x$
					A – 2012					
E_{2012}	36,698.17	10,309.57								
T_{2012}	17.55	6.83	0.207789	0.043176	0.000000	39,188	12.50	0.000	31,194.94	313.546
E_{2012}	36,698.17	10,309.57								
I_{2012}	114.88	170.03	0.238412	0.056840	0.000000	39,188	−29.42	0.004	35,037.46	14.455
E_{2012}	36,698.17	10,309.57								
V_{2012}	3.52	3.10	−0.033600	0.001129	0.000000	39,188	3.89	−0.000	37,091.70	−111.908
T_{2012}	17.55	6.83								
I_{2012}	114.88	170.03	0.457128	0.208966	0.000000	39,188	−84.79	11.377	15.44	0.018
T_{2012}	17.55	6.83								
V_{2012}	3.52	3.10	−0.230647	0.053198	0.000000	39,188	5.35	−0.104	19.34	−0.509
I_{2012}	114.88	170.03								
V_{2012}	3.52	3.10	−0.060655	0.003679	0.000000	39,188	3.64	−0.001	126.60	−3.332
					B – 2012					
E_{2012}	36,672.83	10,303.81								
T_{2012}	17.56	6.83	0.228995	0.052439	0.000000	39,164	11.99	0.0002	30,609.70	345.3601
E_{2012}	36,672.83	10,303.81								
I_{2012}	114.96	170.06	0.317798	0.100995	0.000000	39,164	−77.40	0.0052	34,459.38	19.2549
E_{2012}	36,672.83	10,303.81								
V_{2012}	3.52	3.10	−0.028810	0.000830	0.000000	39,164	3.84	−0.0000	37,010.14	−95.8866
T_{2012}	17.56	6.83								
I_{2012}	114.96	170.06	0.456913	0.208770	0.000000	39,164	−84.72	11.3734	15.45	0.0184
T_{2012}	17.56	6.83								
V_{2012}	3.52	3.10	−0.231189	0.053448	0.000000	39,164	5.36	−0.1048	19.35	−0.5102
I_{2012}	114.96	170.06								
V_{2012}	3.52	3.10	−0.060954	0.003715	0.000000	39,164	3.65	−0.0011	126.73	−3.3483
					A – 2013					
E_{2013}	34,548.85	8,804,062								
T_{2013}	17.09	6,683	0.154528	0.023879	0.000000	44,189	13.03	0.0001	31,070.40	203.5715
E_{2013}	34,548.85	8,804,062								
I_{2013}	112.82	170,496	0.263732	0.069554	0.000000	44,189	−63.63	0.0051	33,012.43	13.6186
E_{2013}	34,548.85	8,804,062								
V_{2013}	3.80	3,418	−0.018643	0.000348	0.000089	44,189	4.05	−0.0000	34,731.43	−48.0282
T_{2013}	17.09	6,683								
I_{2013}	112.82	170,496	0.482973	0.233262	0.000000	44,189	−97.72	12.3215	14.95	0.0189
T_{2013}	17.09	6,683								
V_{2013}	3.80	3,418	−0.180600	0.032616	0.000000	44,189	5.38	−0.0924	18.43	−0.3532
I_{2013}	112.82	170,496								
V_{2013}	3.80	3,418	−0.116038	0.013465	0.000000	44,189	4.06	−0.0023	134.83	−5.7890
					B – 2013					
E_{2013}	34,525.37	8,807,018								
T_{2013}	17.09	6,679	0.154885	0.023989	0.000000	44,159	13.04	0.0001	31,034.40	204.2413
E_{2013}	34,525.37	8,807,018								
I_{2013}	112.71	170,391	0.348371	0.121362	0.000000	44,159	−119.99	0.0067	32,495.86	18.0063
E_{2013}	34,525.37	8,807,018								
V_{2013}	3.80	3,418	−0.011112	0.000123	0.019543	44,159	3.95	−0.0000	34,634.21	−28.6312
T_{2013}	17.09	6,679								
I_{2013}	112.71	170,391	0.416649	0.173597	0.000000	44,159	−68.98	10.6297	15.25	0.0163
T_{2013}	17.09	6,679								
V_{2013}	3.80	3,418	−0.194796	0.037945	0.000000	44,159	5.51	−0.0997	18.54	−0.3806
I_{2013}	112.71	170,391								
V_{2013}	3.80	3,418	−0.115879	0.013428	0.000000	44,159	4.06	−0.0023	134.67	−5.7768
					A – 2014					
E_{2014}	28,172.62	7,015,753								
T_{2014}	16.92	5,562	0.358931	0.128832	0.000000	47,376	8.90	0.0003	20,511.62	452.7414
E_{2014}	28,172.62	7,015,753								
I_{2014}	98.72	158,155	0.305787	0.093506	0.000000	47,376	−95.48	0.0069	26,833.53	13.5647
E_{2014}	28,172.62	7,015,753								
V_{2014}	3.83	3,205	−0.007734	0.000060	0.092306	47,376	3.93	−0.0000	28,237.39	−16.9304
T_{2014}	16.92	5,562								
I_{2014}	98.72	158,155	0.450734	0.203162	0.000000	47,376	−118.15	12.8165	15.36	0.0159
T_{2014}	16.92	5,562								
V_{2014}	3.83	3,205	−0.161061	0.025941	0.000000	47,376	5.40	−0.0928	17.99	−0.2795
I_{2014}	98.72	158,155								
V_{2014}	3.83	3,205	−0.072050	0.005191	0.000000	47,376	3.97	−0.0015	112.32	−3.5556
					B – 2014					
E_{2014}	28,164.29	7,017,463								
T_{2014}	16.92	5,564	0.358288	0.128370	0.000000	47,237	8.92	0.0003	20,520.41	451.8583
E_{2014}	28,164.29	7,017,463								
I_{2014}	98.93	158,384	0.360612	0.130041	0.000000	47,237	−130.30	0.0081	26,583.62	15.9775
E_{2014}	28,164.29	7,017,463								
V_{2014}	3.82	3,200	0.003552	0.000013	0.440188	47,237	3.77	0.0000	28,134.55	7.7884
T_{2014}	16.92	5,564								
I_{2014}	98.93	158,384	0.386896	0.149689	0.000000	47,237	−87.37	11.0127	15.57	0.0136
T_{2014}	16.92	5,564								
V_{2014}	3.82	3,200	−0.178578	0.031890	0.000000	47,237	5.56	−0.1027	18.10	−0.3105
I_{2014}	98.93	158,384								
V_{2014}	3.82	3,200	−0.071292	0.005083	0.000000	47,237	3.96	−0.0014	112.40	−3.5286

Results of the correlation analyses between the parameters for each year indicate a significant decrease in value of the correlation coefficient in compare to the correlation results of the mean monthly values. The results in the case B for each year are slightly better than the ones in A. All of the results are marked as significant, except the one for E2014 vs. V2014, but according to their low r values they are more likely to be unrepresentative to be express by a linear regression line. Linear regression line can be pronounced using coefficient a and b gained in tab. 4 and the equation of linear regression.

Calculation results of the fourth set of data based on 10 minutes time step for winter and summer period

Additional analysis has been done based on the data set of 10 minute time horizon (4), where the calculations are done to establish the relation between selected variables in two periods of each year. Diagrams in fig. 1 show that the wind and solar potential vary during the year. Solar radiation has its maximum during the summer period while wind speed has its maximum during the winter period. Accordingly, two periods of each year are selected to be analysed. Summer period for each year was determined according to the maximum air temperature and maximum peak in electricity demand for three months in a row, June, July and August as show in fig. 1. Winter period is taken to be a period of three months in a row with a lowest air temperature and highest peak in electricity demand. For 2012 and 2014 it is taken to be for December, January and February, while for 2013 is taken to be for January, February and March as show in fig. 1.

Results of the linear correlation and regression are given in tab. 5, 6 and 7. Each table represents each year with case A and B. Case A shows the results for the selected summer period and case B shows the results for winter period.

Table 5. Correlation and regression results for summer and winter period for 2012

x, y	Mean	Std. dv.	r(x, y)	r^2	p	N	a, y	b, y	a, x	b, x
A – 2012										
E_{2012}	44,088.56	10,275.24								
T_{2012}	26.13	3.31	0.662773	0.439268	0.000000	9,074	16.73	0.000	−9,743.73	2,060.366
E_{2012}	44,088.56	10,275.24								
J_{2012}	193.18	213.12	0.318626	0.101522	0.000000	9,074	−98.20	0.007	41,121.05	15.362
E_{2012}	44,088.56	10,275.24								
V_{2012}	2.45	2.28	−0.029784	0.000887	0.004548	9,074	2.74	−0.000	44,417.65	−134.216
T_{2012}	26.13	3.31								
J_{2012}	193.18	213.12	0.537326	0.288720	0.000000	9,074	−712.05	34.647	24.52	0.008
T_{2012}	26.13	3.31								
V_{2012}	2.45	2.28	−0.009193	0.000085	0.381225	9,074	2.62	−0.006	26.16	−0.013
J_{2012}	193.18	213.12								
V_{2012}	2.45	2.28	0.167744	0.028138	0.000000	9,074	2.11	0.002	154.73	15.679
B – 2012										
E_{2012}	42,309.77	9,986.495								
T_{2012}	8.83	3.633	−0.287529	0.082673	0.000000	7,531	13.26	−0.000	49,289.32	−790.333
E_{2012}	42,309.77	9,986.495								
J_{2012}	53.47	94.390	0.036433	0.001327	0.001566	7,531	38.90	0.000	42,103.66	3.855
E_{2012}	42,309.77	9,986.495								
V_{2012}	4.48	3.084	0.060190	0.003623	0.000000	7,531	3.69	0.000	41,436.46	194.895
T_{2012}	8.83	3.633								
J_{2012}	53.47	94.390	0.434655	0.188925	0.000000	7,531	−46.25	11.292	7.94	0.017
T_{2012}	8.83	3.633								
V_{2012}	4.48	3.084	−0.139021	0.019327	0.000000	7,531	5.52	−0.118	9.56	−0.164
J_{2012}	53.47	94.390								
V_{2012}	4.48	3.084	−0.110865	0.012291	0.000000	7,531	4.67	−0.004	68.68	−3.393

Table 6. Correlation and regression results for summer and winter period for 2013

x, y	Mean	Std. dv.	r(x, y)	r^2	p	N	a, y	b, y	a, x	b, x
A – 2013										
E_{2013}	39,240.88	8,640.876								
T_{2013}	25.06	3.702	0.503655	0.253669	0.000000	10,610	16.60	0.000	9,772.74	1,175.675
E_{2013}	39,240.88	8,640.876								
J_{2013}	196.09	218.618	0.360778	0.130015	0.000000	10,610	−161.89	0.009	36,446.21	14.252
E_{2013}	39,240.88	8,640.876								
V_{2013}	2.66	2.301	−0.140073	0.019620	0.000000	10,610	4.13	−0.000	40,642.09	−526.119
T_{2013}	25.06	3.702								
x, y	Mean	Std. dv.	r(x, y)	r^2	p	N	a, y	b, y	a, x	b, x
J_{2013}	196.09	218.618	0.447643	0.200385	0.000000	10,610	−466.55	26.437	23.58	0.008
T_{2013}	25.06	3.702								
V_{2013}	2.66	2.301	0.036142	0.001306	0.000196	10,610	2.20	0.022	24.81	0.058
J_{2013}	196.09	218.618								
V_{2013}	2.66	2.301	0.000447	0.000000	0.963243	10,610	2.66	0.000	195.98	0.043
B – 2013										
E_{2013}	37,472.21	8,459.776								
T_{2013}	10.47	3.188	−0.112984	0.012765	0.000000	12,920	12.06	−0.000	40,810.95	−299.812
E_{2013}	37,472.21	8,459.776								
J_{2013}	60.90	110.088	0.030708	0.000943	0.000481	12,920	41.93	0.000	37,328.50	2.360
E_{2013}	37,472.21	8,459.776								
V_{2013}	5.05	4.090	0.034421	0.001185	0.000091	12,920	4.42	0.000	37,113.00	71.192
T_{2013}	10.47	3.188								
J_{2013}	60.90	110.088	0.408541	0.166909	0.000000	12,920	−68.79	14.108	9.75	0.012
T_{2013}	10.47	3.188								
V_{2013}	5.05	4.090	0.232899	0.054242	0.000000	12,920	1.92	0.299	9.55	0.182
J_{2013}	60.90	110.088								
V_{2013}	5.05	4.090	−0.139772	0.019536	0.000000	12,920	5.38	−0.005	79.88	−3.782

Table 7. Correlation and regression results for summer and winter period for 2014

x, y	Mean	Std. dv.	r(x, y)	r^2	p	N	a, y	b, y	a, x	b, x
A – 2014										
E_{2014}	34,259.62	7,440.386								
T_{2014}	24.78	2.711	0.531300	0.282280	0.000000	9,200	18.15	0.000	−1,867.68	1,418.034
E_{2014}	34,259.62	7,440.386								
J_{2014}	173.95	207.594	0.343010	0.117656	0.000000	9,200	−153.93	0.010	32,121.16	12.294
E_{2014}	34,259.62	7,440.386								
V_{2014}	2.89	2.108	0.045017	0.002026	0.000016	9,200	2.45	0.000	33,800.84	118.917
T_{2014}	24.78	2.711								
J_{2014}	173.95	207.594	0.552724	0.305504	0.000000	9,200	−874.69	42.321	23.52	0.007
T_{2014}	24.78	2.711								
V_{2014}	2.89	2.108	0.183272	0.033588	0.000000	9,200	−0.64	0.142	24.10	0.236
J_{2014}	173.95	207.594								
V_{2014}	2.89	2.108	0.144022	0.020742	0.000000	9,200	2.63	0.001	131.99	14.186
B – 2014										
E_{2014}	27,495.46	6,493.145								
T_{2014}	11.91	3.437	−0.339692	0.115391	0.000000	12,936	16.86	−0.000	35,138.66	−641.666
E_{2014}	27,495.46	6,493.145								
J_{2014}	39.49	77.695	0.105663	0.011165	0.000000	12,936	4.73	0.001	27,146.71	8.830
E_{2014}	27,495.46	6,493.145								
V_{2014}	5.18	4.046	0.113016	0.012773	0.000000	12,936	3.34	0.000	26,556.15	181.372
T_{2014}	11.91	3.437								
J_{2014}	39.49	77.695	0.224492	0.050397	0.000000	12,936	−20.95	5.074	11.52	0.010
T_{2014}	11.91	3.437								
V_{2014}	5.18	4.046	0.036559	0.001337	0.000032	12,936	4.67	0.043	11.75	0.031
J_{2014}	39.49	77.695								
V_{2014}	5.18	4.046	−0.064810	0.004200	0.000000	12,936	5.31	−0.003	45.94	−1.245

The results are different when comparing two periods for each year. It can be seen from the results that the solar radiation has better correlation with electricity demand during summer period. Wind has a positive correlation with electricity demand, which means when wind increases demand increases, as well indicating that the wind could be a good energy resource during the winter time. Although r value is close to 0 and the relation between variables cannot be pronounced with linear regression line. Wind has a good positive correlation during the summer period in 2014 indicating that wind could be a good energy resource during the summer time, as well.

CONCLUSIONS

The aim of this work was to provide the results of the correlation and regression analyses in a short-time scale and question linear relationship between electricity demand and meteorological data. Gained results could help in future energy system planning of the power system with a high share of RES, for the Dubrovnik region, as well as other regions.

Correlation analyses of the first set of data provided results of strong correlation for solar radiation, air temperature and electricity demand distribution between selected years, showing low variation of data in between the years. These results indicate the possibility of a good data forecasting using equations of linear regression line in the 10 minute time step, thus contributing to the future energy system planning. Analyses on wind speed data gained weaker correlation results which means they cannot be pronounced with linear regression line. Air temperature is shown to be a reliable factor used in predicting solar radiation and energy demand.

Linear regression and correlation analyses of the second data set, based on the mean monthly values of the selected variables, gained similar values of correlation coefficient as in the previous studies done for other regions. Results indicate very significant relation of In vs. Vn with $-0.86 < r < -0.81$, meaning that the solar radiation increases as wind speed decreases, which indicates the possibility of combining these two sources in electricity production. 2014 yield representative and significant results for E2014 vs. I2014 with correlation coefficient in value of 0.64 representing solar radiation as a good power source. Correlation of En vs. Vn with $-0.48 < r < -0.23$ indicated negative correlation and was not significant for each year. This study approved combination of wind and sun in electricity production for the selected region. These RES, along with hydro potential, will be considered as the main energy sources for electricity production in our future work of planning the energy system with a high share of RES.

This work went a step forward from previous studies and provided results of the linear regression and correlation between the selected parameters for the 10 minute time step. Correlation results indicate a decrease in correlation coefficient values with a slight improvement when system time delay was considered. The results were more improved when we analysed the relation between the variables for the summer and winter period separately. Our further work will deal with energy plan models and energy market based on the short-term scale. Since the results of this study indicated weak relations between the variables based on the 10 minute time step, especially for the wind speed data, further work needs to be done in order to enhance the integration of RES in the power system production. Additional flexibility will have to be ensured in order to achieve stability in the power system and to accomplish the targets of the electricity production in Croatia by 2020, mentioned in section 0. Additional flexibility can be achieved through additional storage facilities, optimisation using market electricity prices, implementing ICT-tools, as well as combining electricity, heat and transport sector. Correlation analyses between the data will certainly impact the decrease of flexibility requirements, but there will still be the need for some flexibility in the system. Correlation and regression results based on the mean monthly data can be helpful in energy system planning to determine the type of sources used in electricity production, their installed capacities and optimal mix. Results based on the 10 minute data showed that the electricity demand, solar radiation and air temperature can be easily forecasted in a short-term scale. Future energy markets will be arranged in a short-term scale, where ICT-tools will help in energy flow regulation which will be controlled by energy prices. Energy prices will depend on the energy production and energy source, and correlation and regression analyses could provide useful results for future smart energy system planning. In our future work we will deal with energy system planning with a high share of RES in electricity production, based on the short-term scale, in order to reduce the pollution and achieve flexibility and stability of energy system.

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