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Shielding and Thermostatic Control for Optimal Electricity Load Management

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ABSTRACT

Blinds systems, daylighting, natural convection, and shielding thermostat from heating appliances are known to reduce electricity consumption, reduce energy wastage, reduce energy bills, reduce spurious errors in thermostatic controls, reduces over-heating of compressors, reduces the incidence of burnt motors, and fire hazards. Predictive modeling using the multivariate logistic stepwise statistical procedure selects from a set of independent variables of electricity load management survey data gathered from Windhoek City, Namibia to develop the best and optimal model in the study. The results indicate that keeping heat-producing appliances away from the thermostat so that it can give accurate readings is highly interconnected to using blinds systems to reduce inlet heat in summer and heat loss in cold months. Also, small changes in data values can lead to large coefficient estimates and there is a perfect (100.0%) correlation between the dependent and independent variables. In addition, the proportion of the variance explained in the developed model was 97.0%. However, there were also no multicollinearity problems in the data and the developed model was optimal and fairly accurate.

Keywords: blinds systems, daylighting, energy balance, energy savings, energy consumption, waste reduction

1. INTRODUCTION

Electricity supply shortages in the Southern Africa Development Community (SADC) countries prompted demand-side management (DSM) programmes and load shedding that negatively impacted many countries' socio-economic development [1-2]. Namibia secured enough energy beyond August 2016's winter without expecting load shedding. It could acquire 40.0% energy locally and the remaining 60.0% from Zambia and Zimbabwe [3]. Namibia's electricity demand rose significantly in 2012 because of the mining sector, and Eskom supplies over 80.0% of the electricity [4]. Liquid fuel is over 63.0% of the total net energy consumption [5] and flat load curves in the energy sector because of expanding mining activities [6]. Also, Namibia's electricity price and industrial tariffs are high, and South Africa rates are 20.0 to 25.0% lower [7]. The majority of the poor, unemployed, and rural Namibians cannot afford high electricity prices. Also, Namibia's harsh environment and water stress necessitated the Van Eck dry-cooling station in Windhoek [8], and the cooling water needed is the same as the United Kingdom's thermal electricity generation fleet [9]. Furthermore, 18.0% of the United Kingdom's households were fuel poor in 2012. Blinds systems (curtains, shutters, and shade) over windows and doors reduce inlet heat by 50.0% in summer and 25.0% in heat outlets in winter [10]. Daylighting controls offer commercial benefits in the US because around 75.0% of the electricity was consumed in buildings nationwide. Day-lighting reduces by a third total building energy costs [11]. The total electric energy consumed in commercial buildings is between 35.0% and 50.0%. Between 10.0% and 20.0% of the energy used for cooling buildings can be saved by daylighting [12]. Based on building architecture, usage, and energy consumption patterns, daylighting could trim electric lighting between 20.0% and 80.0% [13]. Turning off and dimming lights when not needed saves between 10.0% and 20.0% of the energy used for cooling a building. This also increases employees' productivity and improves the health of building occupants [14].

Also, above US$60 billion was expended annually for electric lighting that comprises over 37.0% average commercial building's total energy consumption [15]. Additionally, over 64 billion square feet of commercial buildings floor space is lit by fluorescent systems, and

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anywhere between 30.0% and 50.0% of the spaces can access daylight either by skylights or through windows. Consequently, millions of electric lighting fixtures can be turned off for some periods of the day for energy savings returns [16]. The United Kingdom and the United States of America have fully developed electricity markets, which effectively control their power systems' peak loads [17]. Also, negative pricing exists in all areas of the United States, which reflects a seasonal distribution and a raised frequency [18]. Price volatility caused by renewable energy injection with government incentives, negative price signals caused by over-supply, and price spikes caused by over-demand, form the basis for electricity load management, future planning, and policy. To balance the impacts of electricity over-supply against over-demand, we formulate a shielding and thermostatic control model using the correlation-covariance method.

2. MATERIALS AND METHODS

2.1 Sample size adequacy

A 5-point Likert scale questionnaire designed for the residential electricity load management survey was validated by a panel of expert judges and used to gather electricity consumption data in Windhoek City, Namibia. Only 127 responses out of the over 300 questionnaires administered were analysed by the statistical analysis for the social sciences (SPSS). Also, the adequacy of the 127 sample size was proven in [19].

Alternatively, the sample size adequacy is proofed using the Poisson distribution. The variance becomes:

$$\sigma = \left\{\frac{1}{N}\sum_{i=1}^{N}(l_i - \mu)^2\right\}^{\frac{1}{2}} \quad (1)$$

where μ is the sample average, l_i average results, and N sample size [20]. We invoke the Normal distribution if the errors are many and independent. The spread of the mean (μ) and the variance (σ), are good estimators of the distribution. For a normal distribution, the probability range is $[\mu - \sigma, \mu + \sigma]$:

$$A(\sigma) = \int_{\mu-\sigma}^{\mu+\sigma} P_G(\mu, \sigma, t)dt = 0.68 \quad (2)$$

where P_G is the probability function and t is time. For 100 measurements, each consisting of 127 measurements, 68.0% lie between $(\mu - \sigma)$ and $(\mu + \sigma)$.

Let $\mu \equiv Np$ (3)

As the probability: $p \to 0$, $N \to \infty$, μ is constant, the binomial distribution approaches a Poisson distribution:

$$P_p(n, \mu) = \frac{\mu^n}{n!}e^{-n} \quad (4)$$

However, the mean and the variance of the Poisson processes are equal. Hence, its occupancy for any sample is $(n)^{\frac{1}{2}}$ and 68.0% is the probability that the true value is within $\left[127 \mp (127)^{\frac{1}{2}}\right]$. The true sample size lies between 116 and 138, so the 127 samples used for the study are adequate for the study.

2.2 Correlation between dependent and independent variables

The correlation coefficient $r_{x,y}$ between $\{y_i\}$ and $\{x_i\}$:

$$r_{x,y} \equiv \frac{\sigma_{x,y}^2}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(x_i-\mu_x)(y_i-\mu_y)}{\left\{\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(x_i-\mu_x)^2\right\}^{1/2}\left\{\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(y_i-\mu_y)^2\right\}^{1/2}} \quad (5)$$

where the mean values of y_i and x_i are given by:

$$\mu_x = \left(\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\right)^{-1}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}x_i = \frac{\beta}{\alpha} \quad (6a)$$

$$\mu_y = \left(\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\right)^{-1}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}y_i = \frac{\theta}{\alpha} \quad (6b)$$

From equations 6a and 6b, we have the variances for the distributions of $\{x_i\}$ and $\{y_i\}$:

$$\sigma_x^2 = \left(\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\right)^{-1}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(x_i - \mu_x)^2 \quad (7a)$$

$$\sigma_y^2 = \left(\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\right)^{-1}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(y_i - \mu_y)^2 \quad (7b)$$

The covariance between x and y:

$$\sigma_{x,y}^2 = \left(\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\right)^{-1}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}(x_i - \mu_x)(y_i - \mu_y) \quad (8)$$

That means, $r_{x,y}^2$ is related to the slope of y_i as a function of x_i [20].

3. RESULTS AND DISCUSSION

The results of the study are shown in Fig. 1 and Tables 1-3. Fig. 1 is a combination of "H" cubic, growth, and logistic regression interaction cross-lines. The attribute of keeping heat-producing appliances from thermostats for accurate readings is independent of gender. This is so because the two parallel lines [21] are standing on 1.0 (male) and 2.0 (female) respectively on the y −axis. Similarly, the observed, cubic, logistic, and growth regression lines are horizontal. These cross-lines indicate that the respondents were rather indifferent in keeping heat-producing appliances away from thermostats, although their levels of agreement hovered around not sure (3) and agree (2).

Table 1 indicates a perfect (100.0%) positive correlation of keeping heat-producing appliances away from thermostats occurring together with using blinds systems to reduce inlet heat in summer and heat loss in cold months. Also, the model covariance indicates the directional relationship of keeping heat-producing devices from thermostats for accurate readings vary concomitantly by 1.8% with the dependent variable. Also, the correlation measures the strength and direction of linear relationships [21].

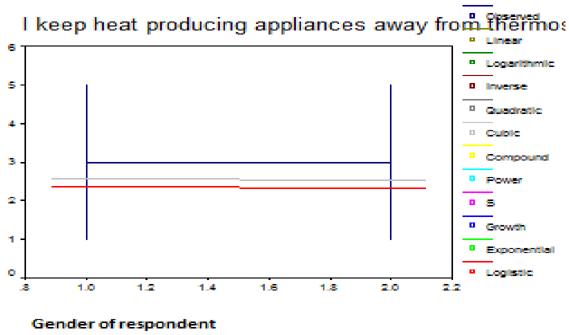

Fig.1 I keep heat-producing appliances away from the thermostat so that it can give accurate readings

Table 2 tests whether there are severe problems of multicollinearity. The small changes in the data values can lead to large changes in the estimates of coefficients. The 0.064 eigenvalue of Dimension 2 that is close to 0.0, indicates that keeping heat-producing appliances away from thermostats and using blinds systems to reduce inlet heat in summer and heat loss in winter are highly interconnected operations. The condition index values greater than 15 indicate possible problems of collinearity [22]. But, Dimensions 1 and 2 of model 1 indicate that there are no collinearity problems in the data because the Condition indices are less than 15 [22]. That means, 3.0% of keeping heat-producing appliances from thermostats give accurate readings in the first Dimension while 97.0% was the explained variance in Dimension 2.

Table 3 indicates the residual statistics of the model, which is the degree to which a model accounts for the variation in the observed data. Residuals check for bias. The standardised residual should be less than -2 or greater than 2. Ordinarily, we expect 95.0% of cases to have standardised residuals within ± 2.0 [22]. For a sample of 127, 6 cases (5.0%) are expected to have standardised residuals outside these limits: Therefore, our sample is what we expected it to be and that it conforms to a fairly accurate model.

TABLE 1. Coefficient Correlations

Model	I keep heat-producing appliances away from the thermostat so that it can give accurate readings
I keep heat-producing appliances away from thermostat so that it can give accurate readings	1.000
I keep heat-producing appliances away from the thermostat so that it can give accurate readings	.018

TABLE 2. Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	I keep heat-producing appliances away from the thermostat so that it can give accurate readings
1	1	1.936	1.000	.03	.03
	2	.064	5.505	.97	.97

TABLE 3. Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.6958	3.6596	2.5154	.50464	121
Residual	-2.6596	3.3042	-.0361	1.04128	121
Std. Predicted Value	-1.591	2.527	.128	1.058	121
Std. Residual	-3.601	4.474	-.049	1.410	121

4. CONCLUSION

Conclusively, shielding and thermostatic control are independent of the gender of respondents, and electricity consumers are either indifferent or oblivious of the costs of spurious dynamic thermostatic control due to energy wastage. There was a perfect (100.0%) positive correlation between keeping heat-producing appliances away from thermostats. Also, using blinds systems to reduce energy loss and thermostatic controls are highly interconnected operations. Therefore, small changes in the data values can lead to large changes in the estimates of the coefficients. Because the condition indices are less than 15 it means that there are no collinearity problems in the data and a fairly accurate model was developed. The 1.8% self-covariance core are single-valued, efficient, anonymous, and weak positive homogenous shifts that are solution vectors and their multipliers of the thermostatic control problem. The drag coefficients and wind profiles could lead to irregular compressor cooling, irregular and localised ambient temperatures. It is also a challenge to be able to trace the principle of “constant safety factor” in thermostatic adaptive response to photo-electro-mechanical stimuli. This is so because neither the photo-electro-mechanical receptor nor the signal transduction process is well understood.

Moreover, shielding thermostat from heat-producing appliances is a good optimal load management practice because incorrect temperature measurements by thermostats make air conditioners overwork and burn their motors as a result.

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