LINEAR MODEL TO PREDICT ENERGY CONSUMPTION USING HISTORICAL DATA FROM COLD STORES

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Abstract- This study wasdeveloped to predict energy consumption, based on the amount fruit stored and environmental factors, using a multiple linear regression model (MLR) in a New Zealand cold store. In this study, linear regression models of a cold storewereselected to show the capability of simple models to reduce margins of error in energy auditing projects. The final MLRmodels developed were based on weeklynumbersavocado and kiwifruit bins and outside temperatures. The comparison between different models demonstrated the amount of stored fruits have more sensitivity than the outside temperatures in cold stores. Comparing actual and predicted energy usage in the studied cold store showed that the MLR model could be fitted to energy usage data and accounted for around 79% of the variance.

Keywords- Energysaving, Energy Auditing,Modelling, Cold Store

I. BACKGROUND

Concern about increasing energy costs andenvironmental impactshas significantly increased in recent years(Azhar et al., 2010).Knowledge about the optimal operation of constrictions is important for decreasing energy consumption. Optimising the energy usage of buildings requiresthe development of energy monitoring and energy auditing systems (Juan et al., 2010). In many energy auditingprojects energy savings are quantified based on the current energy consumption and the previous year'senergy usage(Brandon and Lewis, 1999; Abrahamse et al., 2005). Because ofdifferent factors especially the environmental situations and changing occupation, energy consumptionin different yearscould change significantly. Therefore, modelling energy consumption based on historical data canprovide more accurate energy saving estimations.(Safa et al., 2014). The main objective of this studywasto developasimple model to forecastcold store energy consumption to estimate energy savings during energy auditing projects.

Demand for cold stores is increasing with consumers'increased spending capacity. For example, in the U.S.A. the refrigerated storage industry is expected to grow annually by approximately 3.4% between 2014 and 2019 (Jones Lang LaSalle, 2014). At a global level the frozen foods market was forecast to increase from an estimated $165.4 billion, in 2009, to $199.5 billion by 2014 (Rogers, 2012). Refrigerated and frozen food are the majority (88%) of products stored in cold storage (Jones Lang LaSalle, 2014). However, refrigerationwassimilarlyessential for other sectors, such as pharmaceuticals and petro-chemicals (Rogers, 2012).

According to Evans et al. (2014), there are around 1.5 million cold stores in Europe, including small stores with a capacity of 10-20 $m^3$to large distribution warehouses of hundreds of thousands of m^3. Cold chainscausearound 2.5% of total greenhouse gas emissions through energy usage globally(Guilpart, 2008). In a typical cold store 60-70% of the electrical energy is consumed for refrigeration (Evans et al., 2014).In comparison, 20-50% of household energy consumption, on average, goes into cooling houses and that accounts for 5-15% of the house owner’s carbon footprint (Sustainable Baby Steps, 2015).

The International Institute of Refrigeration (IIR) estimated that cold stores consumed between 30 and 50 kWh/m^3/year (Duiven and Binard, 2002). This energy consumption is likely to increasetwo-fold (Evans and Gigiel, 2007, 2010). There is mounting pressure to reduce energy usage in cooling systems, as it might help save money and decrease carbon footprint outputs(Sustainable Baby Steps, 2015). In fact, reducing energy consumption in cold stores isconsiderable (Evans et al., 2014). This calls for an appropriate strategy that keeps the product cold at a reasonable cost (Rogers, 2012).

Energy saving in cold stores has been investigated in a few projects. The performance of 38 cold stores were inspected in an European research project,to understand how much energy could be saved, areas of common problems and the opportunities that could be implemented toreduce energy usage(Evans et al., 2014). Some of the important factors that neededinvestigationto save energy consumption included air flow, variable speed drives, heat conduction transfer (Mulobe and Huan, 2012), control parameters (Zhang et al., 2009), condenser design (Liu et al., 2010), design of cold store docks (Zhang, 2011)and free cooling systems (Al-Salaymeh and Abdelkader, 2011).

Current information, however, regarding energy savings in cold stores in inadequate. One of the most comprehensive recent studies compared the performance of 34 cold stores in New Zealand. It was estimated that,on average, 15 and 26% of energy savings could be achieved by applying best practice technologiesin cold stores(Werner et al., 2006; Evans et al., 2014). Energy savings of 30–40% werereachable by optimising the energy consumption of cold stores, fixing current facilities and by replacing old facilitieswithmore energy efficient equipment (Evans and Gigiel, 2007, 2010).

Electricity usage has beenanalysed in several studiesusing different types of buildings. However, mostly because ofthe lack of advanced metering technologies in most primary energy modelling studies, monthly power bills were used to investigate energy usage in buildings (Kavousian et al., 2013; Safa et al., 2014).

For the first stepininvestigating energy consumption in cold stores, it was important to determine which parameters were mostsignificantforenergyusage. Kavousian, et al. (2013)categorised four main groups of factors in most buildings: weather and location, appliances and electronic stock, physical characteristics of the building, and occupation.Nevertheless, Issacs, et al. (2010)categoriseddifferent sectores in their survey based on business sector and activities, staff numbers, client numbers and operating periods.Islam et al. (2013) categorised the main environmental factors that would affect the inside temperature and energy consumption in cold stores, including relative humidity (RH), outside temperature, watering and inside RH.

Energy usage in buildingscould be completely different,based ontheir design, construction, occupation and activity, which made it very difficult to classify small numbers of them to represent the majority of similar buildings (Korolija et al., 2013a). A comparison of severalprojects showedthat environmental parameters would be themain parametersused in most studies for predicting energy consumption in most types of buildings. Temperature, humidity and lux levelswere the main environmental factorsthatdirectly affected energy usage in typical buildings (Gugliermetti et al., 2004; Isaacs et al., 2010). However, cold stores were usually insulated much better than other buildingsand had a minimum number of windows. Therefore, outside environmental factors would affect the energy consumption in cold stores less than in other buildings.

Predicting energy consumption in energy savingplans and sustainability projectswas a very important challenge.Several optimisation methods have been developed for energy consumption estimation and a variety of modellingtechniques have been establishedoverthe last decade (Mathews et al., 2001; Rubinstein et al., 2001; Roche and Milne, 2005; Wang et al., 2005; Magnier and Haghighat, 2010; Mukherjee et al., 2010; Pandharipande and Caicedo, 2011; Vakiloroaya et al., 2011; Üçtuğ and Yükseltan, 2012).

II. MODELS

In this study,a cool store closeto Tauranga in the North Island of New Zealand wasinvestigated (Figure 1). Agriculture is the backbone of the district's economy. The warm, humid climate and rich soils provide great conditionforkiwifruit,avocados and citrus fruit production. Energy usage was investigated based on the available historical weekly data. The cold store used had mostly been used to store kiwifruits pallets and avocado bins.

Figure 1. Site locationof the cold storeinvestigated on themap of New Zealand

MLR modelshave been widely used to predict energy consumption projects in different types of buildings(Gugliermetti et al., 2004; Catalina et al., 2008; Neto and Fiorelli, 2008; Lam et al., 2010; Athienitis et al., 2012; Suganthi and Samuel, 2012; Catalina et al., 2013; Korolija et al., 2013b; Safa et al., 2014). Compared with many nonlinear models,MLR models were easier to use and more practical foransweringthe various questions(Catalina et al., 2013) that arose.

For use in the model, it was necessary to select a small number of variables without any selective preference(Safa and Samarasinghe, 2011). A simple model with a high $r^2$was developed through a combination of forward, backward and stepwise regression adjustments. Terms were maintained in the final model if they were significant at p=0.05 (Alvarez, 2009). In the first step, the relationship between energy usage and each input variable was verified with a simple linear regression using the r^2 as the decision criterion. AMLR model was then developed for predicting energy consumption in the cold store as:

$Y=a_0+a_1V_1+a_2V_2+\cdots+a_nV_n$ (1)

where a_0-a_n are the regression coefficients and V_0-V_n are the input (independent) variables.

The model was in a linear form to represent the linear linkbetweenthe outputand the input variables. After running the model, predictions on the data were estimated. In this study, the model wasdeveloped with a minimum possible number of variables,to capture energy consumption in as simple a form as possible. After investigating several variables, outside temperature and number of stored kiwifruit and avocado binswere selected as the independent variables with which to develop the models. Theweekly temperature was collected from a national weather database (NIWA) and property managers provided the number bins.

Several methods of error estimation were proposed. The mean square error (MSE) over all the training patterns (Eq. 2) was the most commonly used error indicator. MSE was very handyfor comparing different models; as it showeda network's capability to predict the output variables. The MSE can be written as:

$$MSE = \frac{1}{2N}\sum_{i}^{N}(t_i - z_i)^2 \quad (2)$$

wheret_i and $z_i$were the actual and predicted outputs for the i^{th} training pattern, and N is the total number of training patterns (Samarasinghe, 2007; Catalina et al., 2013). The root mean square error (RMSE) was another error estimation method, which showed the error in the units of the actual and predicted data.

In this study,severalmodelswith different input variables were developed and compared to find the best fit between the predicted data and the actual data. Comparing different models showed thata model developed based on stored fruit bins can predict energy usage better than the model with environmental factors as the input variable. As shown in Figure 2, the final model was developed based on 104 weeksof available historical data.It was notable that the model developed,based only on outside temperature and number of stored kiwifruit pallets and avocado bins,was accurate with a very high correlation coefficient between the actual and predicted energy usage. However, differences between models with two independent variables (number of stored kiwifruit pallets and avocado bins) and three independent variables (temperature and number of stored kiwifruit pallets and avocado bins) showedthatthe number of stored kiwifruit pallets and avocado binscan improve the correlation coefficients between the actual and predicted energy usage.

III. RESULTS

The results showed that the weekly energy usage in cold stores can be predicted by the outside temperature and the numbers of stored pallets. The energy usage mostly depended on the number of kiwifruit pallets and the number of avocado bins. The low usage in summer would be influenced mostly by the harvestingseason for avocado and kiwifruit. It should be noted that energy usage in the cold stores would also be affected by a number of other parameters. Figure 2 shows that the predicted and actual data matched in most cases.

Several different models were developed to find the best model to predict energy usage based on the numbers of kiwifruit pallets, numbers of avocado bins, and the outside temperature.Comparing different models showedthat the numbers of kiwifruit pallets and the numbers of avocado bins can be used to predict energy usage accurately; however, including the outside temperature improved the accuracy of the prediction and reducedthe margin of error further. The final linear multiple regression model was developed based on available weekly data overalmost two years. The results show a final MLR model could be fitted to the energy usage data and estimatedapproximately 79% of the variance (Figure 2).

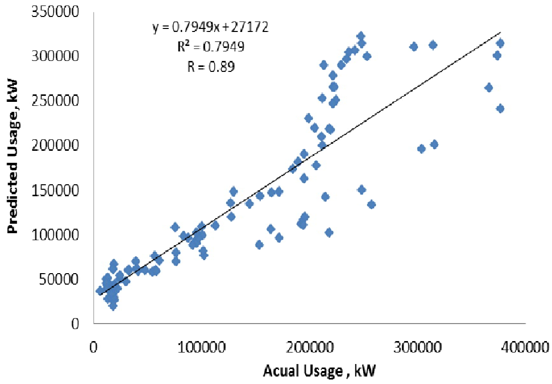

Figure 2 Relationships between observed and predicted energy usage fromthe multiple linear regression model

The energy usage predicted by the model = 182269.7 + (12.79 * numbers of kiwifruit pallets) – (20.7* numbers of avocado bins) - (7005.25 * outside temperature). Figure 3 shows the how actual and predicted data matched together. It apeared the main difference would be in the peaks of energy usage. It was clear that the predicted and actual data were correlated significantly and the simple linear model can predict energy use with an acceptable error.

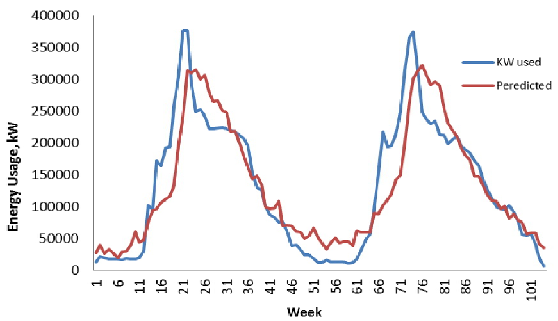

Figure 3 Actual and predicted energy usage during 2011 and 2012 based on weekly data

As mentioned before, few models with different input variables have been investigated. These models; however, showedthat the stored bins would be the most important factors affecting energy usage in cold stores. Moreover, the outside temperature, even in fully insulated cold stores, would also be an important factor. Multiple linear regression models could be fitted to the energy usage andestimatedbetween 75%, and 79% of the variance for the model based on the stored avocado and kiwifruit bins and pallets and the model based on outside temperature and number of bins, respectively(Figure 3). The final RMSEs were calculated as 34,885, and 32,640 kW.hforthe two models,respectively (Table 1).

Table 1. Model equations and RMSE (kW.h

Input variables	Equation	RMSE
Avocado bins+ kiwifruit bins	87561.6+ (31.68* Tem) - (3405.34*FTE)	34885
Temperature + avocado bins+ kiwifruit bins	182269.7 + (12.79 * Kiwifruit pallets) – (20.7* Avo bins) - (7005.25 * tem))	32640

The high sensitivity forthe numbersof stored bins showed it would be too difficult to develop a model estimate even forsimilar cold stores. The final linear model was simple (three variable regression model) compared with nonlinear models. It accurately compared the actual and predicted energy usage and estimated energy auditing in buildings.

CONCLUSION

This study presented anenergy prediction method to estimate energy savings in cold storesshould be investigated based on different factors. The results showedthat the linear model with basic inputvariablescan predict energy usage within acceptable errors. The accuracy of the historical data would be a critical factor in developingamodel with a minimum margin of error. The main challenge of this method was finding accurate data overan acceptable period of time. The models show stored fruits were the main factors for predicting energy usage in cold stores.

This linear model can be used by owners, managers, and energy consultants to control and audit energy usage in cold stores. The method used in this study can be developed for other similar projects. Future studies to compare other modelling methods and other input variables is strongly recommended.

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