Life Cycle Greenhouse Gas and Energy Cost Optimization for Manufacturing Sector in Thailand

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Abstract

Energy consumption in the Thai manufacturing sector covers around 36% of the total energy demand. The high energy consumption causes many problems such as energy limitation, energy cost, and GHG emissions. Concerning the sustainable development for the manufacturing sector, the energy consumption should consider not only the energy demand but also energy cost and GHG emissions. A multi-objective optimization model for energy consumption in the manufacturing sector was developed from a predictive model and a second-order Taylor series expansion. GHG emissions were calculated based on an LCA concept. The energy demand in the target year 2020 was predicted as BAU, and the multi-objective optimization model was used to find the optimal energy consumption which allocated energy resource type in each manufacturing subsector for minimising energy cost and GHG emissions. The optimal total energy consumption for 2020 was found to be 29,665 ktoe, which is less than that predicted by BAU by 2,542 ktoe (8%). This is equal to a reduction of 11,520 GgCO_2e GHG, overachieving the Thailand NAMA roadmap 2020 for energy in the manufacturing sector. The results can be used for allocating the energy resources for low GHG emissions and total energy cost while maintaining adequate energy demand.

Keywords:

life cycle greenhouse gas emissions, energy cost, optimization, manufacturing sector, thailand

1. Introduction

It is well known that energy is important for all economic sectors, i.e., electricity, transportation, industry, households, agriculture and commerce; therefore, energy plays significant roles in human life and economic development. During the past decade, Thailand's energy consumption has mainly been in the transportation and manufacturing sectors, which each account for around 34-37% of total energy consumption in the country. The industrial sector plays an important role in the development of Thailand's economy, and its rapid growth has influenced the increase in Thailand's energy demand. The energy consumption in the industrial sector grew continuously from 16.9 million tonne of oil equivalent (Mtoe) in 2001 to 27.9 Mtoe (approximately a 65% increase) in 2014 (Energy Statistics & Information, Ministry of Energy).

Energy is the most important influence on environmental impact, especially in the form of Greenhouse Gas (GHG) emissions, which increase the earth's temperature, leading to global warming and climate change (Lallanilla, 2015). Thailand's First Biennial Update report or Third National Communication reported by the Office of Natural Resources and Environmental Policy and Planning (ONEP) shows the country's GHG emissions in the year 2011 in units of million tonnes of carbon dioxide equivalent ($MtCO_2e$). The highest GHG emissions were found to be from the energy sector, which energy from manufacturing industries and construction sector account for 44.52 $MtCO_2e$, that is, 20% of GHG emissions in the energy sector.

The United Nations Framework Convention on Climate Change (UNFCCC), an international convention started in 1992 with the objective is to stabilize the greenhouse gas concentrations in the atmosphere so that they remain at a level that would prevent dangerous human-induced interference with the climate system (UNFCCC, 2009), and more than 150 countries also ratified at the 'Earth Summit' in Rio de Janeiro, Brazil. In 2010, UNFCCC encouraged the developing countries listed as non-Annex I parties to propose nationally appropriate mitigation actions (NAMA) with a greenhouse gas reduction target by the year 2020. Thailand's NAMA Pledge proposes an action plan to reduce GHG emissions by between 7 and 20 percent below business-as-usual (BAU) projections for 2020 in the energy and transportation sectors (UNFCCC, 2009.). In October 2015, Thailand's Intended Nationally Determined Contributions (INDCs) initiated effort to reduce GHG emissions by 20 percent from the projected BAU level by 2030, starting from the year 2020 (UNFCCC, 2015b). Moreover, in December 2015, UNFCCC agreed with the 'Paris agreement' at the Conference of Parties (COP21), which aims to keep any future global temperature rise well below 2 degrees Celsius above pre-industrial levels and attempts to limit the temperature increase to below 1.5 degrees Celsius (UNFCCC, 2015).

There are many models for energy system analysis (Filar and Krawczyk, 2009; Suganthi and Samuel, 2012). The first category is that of the simple mathematical model used to analyse energy demand, energy supply, energy conversion and more efficient technologies in both short-term and long-term periods, such as the Model for Long-Term Energy Demand Evaluation (MEDEE), which is a simulation model commonly used in the European Union to evaluate the long-term energy demand of a country. Another Model is the Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE), which is a linear programming model used to optimise energy supply and technologies developed by the International Institute for Applied Systems Analysis (IIASA) (Agnew et al., 1979; Hainoun et al., 2010). Another well-known model is MARKAL, or MARKet ALlocation, which is a least-cost linear programming model developed by the International Energy Agency (IEA) (Suganthi and Samuel, 2012; Krzemien, 2013;

Taylor et al., 2014). Such models have been applied successfully. Bruno Lapillonne (1980) analysed and forecasted the U.S. energy demand for 1985 and 2000 based on the MEDEE model. Furthermore, MESSAGE model was applied to project the energy system (supply and demand) for Syria (Hainoun et al., 2010). Comodi et al. (2012) used the TIMES model to analyse and develop a 25-year energy policy for three sectors (households, transport, and the public sector) for the town of Pesaro in central Italy. The U.S. energy security on the short and long-term future was evaluated, analysed, and helped to be maintained by using the linear programming MARKAL model (Victor et al., 2017).

The second widely used model category is that of mathematical models developed for systems concerned with more than one dimension, such as the Long-range Energy Alternatives Planning System (LEAP) and Optimization model. LEAP is a software tool which has been developed by the Stockholm Environment Institute to analyse energy policy and assess the climate change mitigation (Suganthi and Samuel, 2012; Heaps, 2016). The Optimization model is a model solving single-level, bi-level or multi-level problems and also finding the optimal solution (Zhang et al., 2015). Huang et al. (2011) analysed and forecasted the energy demand and supply system in Taiwan based on the LEAP model. Su et al. (2015) used a Multi-objective optimization model to analyse the energy structure of Beijing by minimizing the energy cost, energy consumption, and environmental impact. Falke et al. (2016) applied a multi-objective optimization model to optimise the annual costs of energy supply and CO2 emissions in Germany.

This present study aims to balance the energy consumption in the Thai manufacturing sector in multiple dimensions to support the sustainable development strategy of the Thai government by being concerned with energy balance, economic and environmental impact in term of GHG emissions, according to the Life Cycle Assessment (LCA) concept. A multi-objective optimization mathematical model is developed for the Thai manufacturing sector by using together a predictive model of energy demand and a second-order Taylor series expansion of energy cost. The results are the optimal energy resource types for each manufacturing subsector for the target year 2020 which minimize the energy cost and the GHG emissions from energy in the manufacturing sector. These results are used as a guideline for allocating the energy resources for low GHG emissions and total energy cost while maintaining adequate energy demand.

2. Methodology

In this study, a predictive model and a multi-objective optimization are applied for minimizing a total energy cost and GHG emissions of energy consumption in the Thai manufacturing sector subject to constraints for energy resource types, energy in each subsector and energy of a specific resources in each subsector. Fig. 1 shows a simple block diagram of the proposed method. Energy consumption data for each Thai manufacturing subsector and the energy cost data collected in time series during 2007–2014 are used for developing predictive models of the energy demands of each energy resource type, each subsector and a specific resource in each subsector. A linear regression analysis was used for fitting the models of future energy demands.

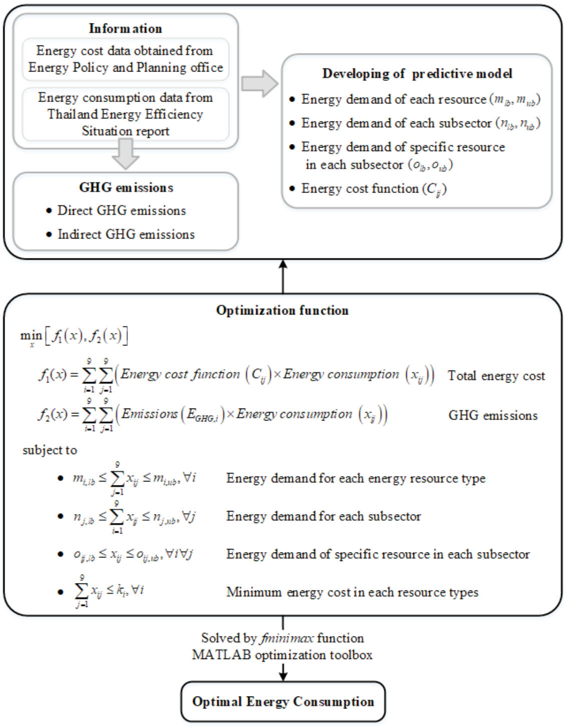

Fig. 1 Overall block diagram of the calculation algorithm for the proposed multi-objective optimization.

In the study, the energy cost of each Thai manufacturing subsector is assumed to be a function of the energy consumption of specific resources in that subsector. The energy cost function is expressed by a second-order Taylor series expansion model for which the model coefficients were obtained from a regression technique, the lsqcurvefit function of the MATLAB optimization toolbox. The proposed multi-objective optimization functions are formulated by the use of the predictive model and GHG emissions (both direct and indirect GHG emissions) and later solved by the fminimax function of MATLAB optimization toolbox. Details of the models and optimization function are given in the following subsections.

2.1 Predictive model of energy demands

Thailand manufactures can be divided into nine subsectors, and there are nine energy resource types; i.e., coal, liquefied petroleum gas (LPG), other oil, fuel oil, diesel oil, natural gas, electricity, renewable energy, and traditional renewable energy; used in each subsector; i.e., food and beverages, textiles, wood and furniture, paper, chemical manufacture, non-metallic manufacture, basic metal manufacture, fabricated metal manufacture, and others. Unleaded gasoline (ULG) and kerosene are taken into account in energy resource type of "other oil" because they constitute less consumed energy. The regression analysis technique used in the following is a statistical tool to assess the relationships between two or more variables. It is widely used to evaluate variables or parameters (Sykes, 1993; sphweb.bumc.bu.edu). A linear model in the form of Eq. (1) is applied for predicting the upper bound (ub)/lower bound (lb) of energy demands for each energy resource type (m), each subsector (n), and specific resource in each subsector (o):

$$\begin{aligned} \bar{Y} &= \beta_0 + \beta_1 X \\ \bar{Y}_{lb} &= \bar{Y} + \delta^- \\ \bar{Y}_{ub} &= \bar{Y} + \delta^+ \end{aligned} \tag{1}$$

where $\bar{Y}$ is the vector of predicted energy demands, X is the vector of time in years, β_0 and β_1 are coefficient matrices obtained by linear regression of energy demand data, δ^- is a minimum negative error between the actual and predicted values of energy demands, δ^- is a maximum positive error between the actual and predicted values of energy demands, and the subscripts lb, ub indicate the lower bound and upper bound, respectively.

2.2 Energy cost function calculation

The energy cost function mainly depends on the energy consumption in each subsector. In this work, a cost function equation with a second-order Taylor series expansion is used, as given in Eq. (2):

$$C_{ij} = b_0 + \sum_{j=1}^{9}(b_j x_j) + \sum_{j=1}^{9}\sum_{k=j+1}^{9}(b_{jk}x_j x_k) + \sum_{j=1}^{9}(b_{jj}x_j^2) \quad (2)$$

Where C_{ij} is the energy cost function of the ith energy resource in the j^{th} subsector (Baht per ktoe), b_0,b_j,b_{jk},b_{jj} are model coefficients of the energy cost function, and x_j x_k is the energy consumption in each subsector (ktoe).

Historical data of energy cost and energy consumption in Thailand during the years 2007-2014 were used to calculate the cost function coefficients (b_0,b_j,b_{jk},b_{jj}) by a regression analysis with lsqcurvefit function in the MATLAB optimization toolbox for all 81 energy cost functions. The energy cost of the renewable energy and traditional renewable energy were determined from Sujeetha Selvakkumaran (Selvakkumaran et al., 2015), while remaining energy costs were obtained from the Energy Policy and Planning office (EPPO, 2015)

2.3 GHG emissions calculation

The environmental impact of concern in this study was that contributed by GHG emissions and was analysed by using Life Cycle Assessment (LCA). LCA is a tool to evaluate the life cycle environmental impact of a product or service (ISO 14040, 2006). In this case, the environmental impact from GHG in LCA considered both direct GHG emissions and indirect GHG emissions, that is to say, Cradle to Gate (C to G) GHG emissions. The Cradle to Gate emissions are those which come from the raw material acquisition phase which are included the energy production and transportations.

All direct GHG emissions were calculated based on the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Table 2.3 Volume 2 Intergovernmental Panel on Climate Change) (IPCC, 2006). Meanwhile, the indirect emissions of each energy resource type were calculated from the Thai National Life Cycle Inventory Database and Ecoinvent Database version 2.0. The GHG emissions from each gas were characterized as CO2 equivalent by using Global Warming Potential (GWP) given in the Fourth Assessment Report of IPCC (AR4) (IPCC, 2007). The total GHG emissions were calculated using Eq. (3).

$$E_{GHG,i} = Direct\ Emission_i + Indirect\ Emission_i(CtoG)$$
$$= (x_f \times EF_{GHG,f} \times GWP) + (E_i \times GWP) \quad (3)$$

where is the total GHG emissions of the i^{th} energy resource (Gigagram of Carbon dioxide equivalent per ktoe: $GgCO_2e$/ktoe), x_f is the amount of energy consumption of fuel f (Terajoule: TJ), $Ef_{GHG,f}$ is the default emission factor of GHG for fuel f per TJ based on the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006), E_i is the amount of GHG emitted by the ith energy resource based on the Thai National Life Cycle Inventory Database and the Ecoinvent Database version 2.0, and GWP is the Global Warming Potential per unit of energy or fuel based on the Fourth Assessment Report of IPCC (AR4) (IPCC, 2007).

2.4 Formulation of multi-objective optimization function

Multi-objective optimization is a tool to find the optimal solution for a problem involving more than one objective function subject to a set of constraints; an objective function is a quantitative measure of the performance of the system that can be used to either minimise or maximise the problem depending on the objective (Wisconsin Institutes for Discovery, 2014). In this study, optimization function was developed to find an energy consumption solution that optimally allocates energy resource types into various manufacturing subsectors so as to balance economic and environmental viewpoints. There are two objectives which are formulated as a function of total energy cost and GHG emissions. The constraints are the total energy consumption in each energy resource type, the total energy consumption in each subsector, and the energy demand regarding specific resources in each subsector as determined by the forecasting. Details of formulations of objectives and constraints are given in following subsections.

2.4.1 Objective functions

The objective in this study is to minimize the total energy cost and GHG emissions, as shown in Eq. (4):

$$\min_{x}[f_1(x), f_2(x)] \tag{4}$$

There are two objective functions, one related to economics and the other to the environment, as shown in Eq. (5) and Eq. (6). The Economic objective function (f_1) represents a sum of energy cost for Thai manufacturing sectors and is defined as follows:

$$f_1(x) = \sum_{i=1}^{9}\sum_{j=1}^{9}(C_{ij}x_{ij}) \tag{5}$$

where x_{ij} is the energy consumption of the ith energy resource in the j^{th} subsector (ktoe) and is the energy cost of the i^{th} energy resource in the j^{th} subsector (Baht/ktoe), expressed by Eq. (3).

The Environmental objective function (f_2) represents a sum of the GHG emissions released from energy consumption in Thai manufacturing sectors and is defined as follows:

$$f_2(x) = \sum_{i=1}^{9}\sum_{j=1}^{9}(E_{GHG,i}x_{ij}) \tag{6}$$

where $E_{GHG,i}$ are the total GHG emissions of the i^{th} energy resource ($GgCO_2e$/ktoe), expressed by Eq. (3).

2.4.2 Constraints

Constraints for energy resource types: these constraints are added to the optimization to represent the possible availability of each energy resource type, as defined in Eq. (7):

$$m_{i,lb} \le \sum_{j=1}^{9} x_{ij} \le m_{i,ub}\ ,\forall i \tag{7}$$

Constraints for energy in each subsector: these constraints represent difference in the usage amount of energy resource in each manufacturing subsector, as defined in Eq. (8):

$$n_{j,lb} \le \sum_{j=1}^{9} x_{ij} \le n_{j,ub}\ ,\forall j \tag{8}$$

Constraints for energy of specific resource in each subsector: the limitation of the ith energy resource in the jth subsector is defined in Eq. (9):

$$o_{ij,lb} \le x_{ij} \le o_{ij,ub}\ ,\forall i \forall j \tag{9}$$

Note that the upper bounds (and) and lower bounds (and) of the constraints were calculated using Eq. (1).

3. Results and Discussion

3.1 Predictive solutions of energy demand The upper bound and lower bound obtained from the regression analysis techniques of energy demand for each energy resource type, each subsector, and specific resource in each subsector. Table 1 shows the upper bound and lower bound of energy demand for a specific resource in each subsector predicted for 2020 (ktoe).

Table 1 Upper bound and lower bound of energy demand for a specific resource in each subsector predicted for 2020 (ktoe).

Energy resource type	UB/LB	Manufacturing subsector								
		Food & Beverages	Textiles	Wood & Furniture	Paper	Chemical	Non-metallic	Basic Metal	Fabricated Metal	Others
Coal	UB	110	0	0	0	426	4,307	586	0	689
	LB	0	0	0	0	16	2,763	55	0	0
LPG	UB	49	19	1	10	277	72	146	75	182
	LB	38	9	0	6	220	13	101	17	123
Other Oil	UB	7	5	3	9	27	11	11	23	91
	LB	0	1	0	3	2	5	4	5	9
Fuel Oil	UB	261	0	0	1	56	16	97	76	281
	LB	152	0	0	0	0	0	73	58	99
Diesel Oil	UB	1,991	252	346	296	464	514	447	599	2,247
	LB	1,372	189	259	222	275	381	327	446	1,643
Natural Gas	UB	95	145	21	811	1169	692	624	0	217
	LB	0	39	16	702	975	432	492	0	0
Electricity	UB	1,542	590	207	249	1,082	689	724	1,926	119
	LB	1,450	497	184	226	988	548	553	1,676	102
Renewable Energy	UB	7,760	0	0	692	451	419	0	0	0
	LB	7,223	0	0	618	391	19	0	0	0
Traditional Renewable Energy	UB	1,810	10	87	0	0	501	0	0	0
	LB	1,187	6	0	0	0	206	0	0	0

3.2 GHG emissions resulting from energy resources

The GHG emissions resulting from use of each energy resource type for Thai manufacturing sectors are calculated, with direct, indirect and total GHG emissions in terms of GgCO2e per ktoe. There are no direct GHG emissions from electricity consumption because all of the GHG emissions resulting from electricity consumption occur at the power plant. Here, renewable energy and traditional renewable energy come from the raw material from agriculture waste or are renewable sources which are assumed to have no indirect GHG emissions.

3.3 Changing of energy consumption structure after optimization

The results of optimising energy consumption in Thai manufacturing sectors are shown in Table 2. These results show optimal energy consumption for each energy resource type in each manufacturing subsector in the target year 2020, with this optimal energy consumption structure leading to the minimal total energy cost and total GHG emissions.

In these optimised results, the total energy consumption demand for 2020 is predicted to be 29,665 ktoe, an increase of about 6% from year 2014. The highest consumption of energy by resource type comes from renewable energy, followed by electricity, diesel, and coal (30.7%, 21.3%, 18.4%, and 10.0% of total energy consumption, respectively).

Fig. 2 shows details of the proportion of energy consumption by each energy resource type for the year 2014 and the optimization results for the target year 2020. In these results, the proportion of renewable energy and diesel both increase for the year 2020, due to policy support for renewable energy and the trend that sees decreasing of crude oil price. The renewable energy consumption is mainly in the food and beverage subsector. It is predicted to increase from 23% in 2014 to 31% of total energy consumption by 2020. Such predicted renewable energy consumption aligns with the Thailand Alternative Energy Development Plan (AEDP), which aims to increase the use of renewable energy since the latter is considered to reduce GHG emissions from waste management (landfill and incineration).

Table 2 Optimal energy consumption in the manufacturing sector for 2020 by manufacturing subsector and energy resource type (ktoe).

Energy resource type	Manufacturing subsector									
	Food & Beverages	Textiles	Wood & Furniture	Paper	Chemical	Non-metallic	Basic Metal	Fabricated Metal	Others	Total
Coal	0	0	0	0	16	2,763	55	0	122	2,956
LPG	49	9	1	6	220	13	146	17	123	584
Other Oil	0	1	3	9	27	11	4	5	9	69
Fuel Oil	152	0	0	0	0	0	87	76	281	596
Diesel Oil	1,372	189	298	222	464	381	447	446	1,643	5,462
Natural Gas	95	133	21	702	1,029	432	492	0	0	2,904
Electricity	1,450	497	184	226	988	548	645	1,676	119	6,333
Renewable Energy	7,760	0	0	618	391	325	0	0	0	9,094
Traditional Renewable Energy	1,443	6	0	0	0	218	0	0	0	1,667
Total	12,321	835	507	1,783	3,135	4,691	1,876	2,220	2,297	29,665

In Thailand, coal is mainly consumed in the non-metallic manufacturing subsector and the amount of coal used is predicted to decrease from 17% of total energy consumption in 2014 to 10% of total energy consumption for 2020. Meanwhile, natural gas and electricity consumption in the manufacturing sector remain steady at about 10% and 21% of total energy consumption, respectively.

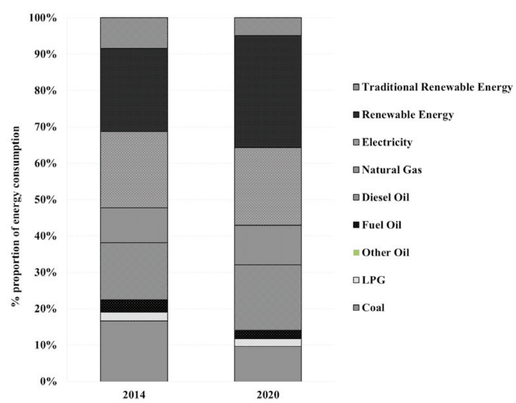

Fig.2 Proportion of energy consumption for each energy resource type in Thailand for the year 2014 and the optimization results for the year 2020.

The three manufacturing subsectors with the highest energy consumption are Food and Beverage (42%), Non-metallic manufacture (mainly cement industry) (16%) and Chemical manufacture (11%), as shown in Fig. 3.

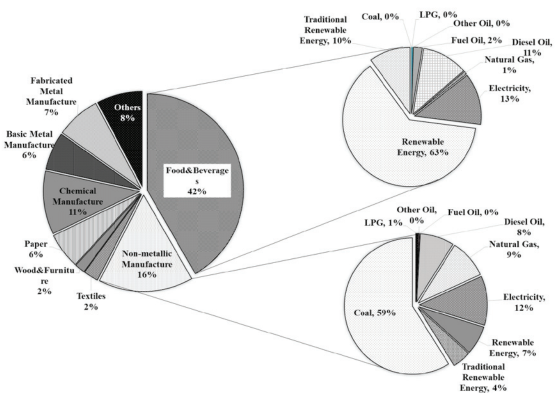

Fig. 3 Results of optimization of energy consumption proportion by manufacturing subsector.

The Food and Beverage subsector consumes the greatest amount of energy among all manufacturing subsectors with about 42% of total energy consumption being used there. Of this, 63% of energy use is in the form of renewable energy. This is because this subsector uses its agriculture waste from raw material — e.g., bagasse, paddy husk, fuel wood, municipal solid waste (MSW) — to produce power in the form of electricity, biogas, and heat (Department of Alternative Energy Development and Efficiency, 2015).

The highest amount of energy consumption by energy resource type in the Non-Metallic manufacturing subsector is coal. However, coal consumption in this subsector was predicted to decline from 3,940 ktoe to 2,763 ktoe (64% to 59% of energy consumption in the Non-Metallic manufacturing subsector). This results due to the main industry in this subsector being the cement industry, which aims to reduce GHG emissions by using partial fuel from biomass and waste (from industry or agriculture).

3.4 Overall energy consumption and energy intensity

The BAU projections of total energy consumption up to the year 2020 are developed from the predictive model of energy demand (the summation of 81 models of specific resources in each subsector) and based on historical data from 2007 to 2014. Based on the predictive model, the total energy demand for the manufacturing sector was projected to be 32,207 ktoe. The optimization results show that this energy consumption can be reduced by 2,542 ktoe, or about 8%, compared to the energy consumption in BAU case, as shown in Fig. 4. In addition, the optimization results show that GHG emissions can also be reduced by 11,520 GgCO2e, or 11% reduction, compared with BAU. Such reductions would overachieve those proposed by the NAMA roadmap 2020 target, which aims to eliminate at least 4,255 GgCO2e from energy use in the manufacturing sector (Limmeechokchai, 2014).

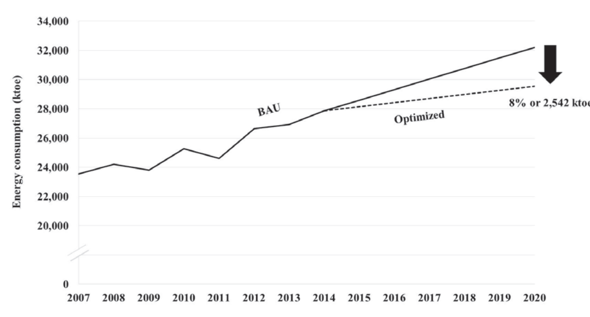

Fig. 4 Comparison of total energy consumption obtained from optimization results and those which would be obtained with BAU.

The Energy Intensity (EI), which is the energy per unit of Gross Domestic Product (GDP), is used to show the energy performance in term of economic growth. In this study, EI values are calculated based on GDP from the Office of the National Economics and Social Development Board (NESDB) (osthailand.nic.go.th), while the GDP is forecasted to increase by 3.94% per year following the EE plan 2015–2036 (EPPO, 2015). The optimization results show that the EI values for the manufacturing sector for the year 2020 can be reduced 16% relative to the values which were obtained in 2014.

4. Conclusions and Recommendations

A multi-objective optimization to find the optimal energy consumption in Thailand was developed using regression analysis and a second-order Taylor series expansion. The model aims to find the optimal energy consumption in the manufacturing sector, allocating the energy resource types into each manufacturing subsector to balance economic and environmental points of view. The optimization results show that total energy consumption is predicted to be reduced by 2,542 ktoe, which is 8% of total energy consumption, compared to BAU. The subsectors with the highest energy consumption are Food and Beverage, Non-metallic manufacture (mainly cement industry), and Chemical manufacture. The highest proportion of energy comes from renewables, followed by electricity, diesel and coal. This optimal results can reduce GHG emissions in the year 2020 by 11,520 $GgCO_2e$, or 11%, relative to BAU — an achievement greater that proposed by the Thailand NAMA roadmap 2020 target. These results could be used as an industrial guideline for allocating energy resources according to less GHG emissions, high energy efficiency, and overall energy cost.

Optimization results from this study show the proportion of energy that is renewable increasing. The government should support renewable energy allocation so as to prevent the shortage of renewable resources, because renewable resource demands are also increasing for the production of electricity and heat. Other renewable resources such as Municipal Solid Waste (MSW) and biogas from wastewater treatment should be considered as additional resources. Waste management policy should support the aggregation of solid waste in order to manage such waste for use as an energy resource; possibilities include the separation of organic waste and other recyclable waste.

Finally, this work also supports policy makers in order to achieve the stated target of reducing GHG emissions and in order to also attain suitable energy management for the manufacturing sector in Thailand.

5. Acknowledgements

This study has been supported by the Institution Research Fund Grant (The Thailand Research Fund) (IRG5980004), and the Faculty of Engineering, Kasetsart University.

6. References

Agnew, M., Schrattenholzer, L., and Voss, A., 1979. A model for energy supply systems alternatives and their general environmental impact. IIASA Working Paper.

Comodi, G., Cioccolanti, L., Gargiulo, M., 2012. Municipal scale scenario: Analysis of an Italian seaside town with MarkAL-TIMES. Energy Policy, Modeling Transport (Energy)

Demand and Policies 41, 303–315.

Department of Alternative Energy Development and Efficiency (DEDE), Ministry of Energy. Alternative Energy Development Plan: AEDP2015. URL www.dede.go.th/download/files/AEDP2015_Final_version.pdf (accessed 26.4.16).

Department of Alternative Energy Development and Efficiency (DEDE), Ministry of Energy. Energy Statistics & Information. 2015. URL http://www.dede.go.th/ewt_w3c/ewt_news.php?nid=42079 (accessed 26.1.16).

Energy Policy and Planning office (EPPO), Ministry of Energy. Energy Efficiency Plan; EEP 2015. URL http://www2.eppo.go.th/encon/EEP2015/index.html (accessed 26.4.16).

Falke, T., Krengel, S., Meinerzhagen, A.-K., Schnettler, A., 2016. Multi-objective optimization and simulation model for the design of distributed energy systems. Applied Energy 184, 1508–1516.

Filar, J.A., Krawczyk, J.B., 2009. MATHEMATICAL MODELS – Volume II. Encyclopedia of Life Support Systems (EOLSS) Publications.

Greenhouse Gases and Temperature [WWW Document], n.d. URL http://ete.cet.edu/gcc/?/globaltemp_ghgandtemp/ (accessed 8.3.17).

Hainoun, A., Seif Aldin, M., Almoustafa, S., 2010. Formulating an optimal long-term energy supply strategy for Syria using MESSAGE model. Energy Policy, Energy Security - Concepts and Indicators with regular papers 38, 1701–1714.

Heaps, C.G., 2016. Long-range Energy Alternatives Planning (LEAP) system. Stockholm Environment Institute. Somerville, MA, USA. URL https://www.energycommunity.org/default.asp?action=introduction (accessed 8.3.17).

Huang, Y., Bor, Y.J., Peng, C.-Y., 2011. The long-term forecast of Taiwan's energy supply and demand: LEAP model application. Energy Policy, Asian Energy Security 39, 6790–6803.

Introduction to Optimization | NEOS [WWW Document], n.d. URL https://neos-guide.org/content/optimization-introduction (accessed 8.3.16).

Introduction to the Convention First steps to a safer future: Introducing The United Nations Framework Convention on Climate Change. URL http://unfccc.int/essential_background/convention/items/6036.php (accessed 3.8.17).

IPCC - Task Force on National Greenhouse Gas Inventories 2006 [WWW Document], n.d. URL http://www.ipcc-nggip.iges.or.jp/public/2006gl/ (accessed 4.3.16).

IPCC Fourth Assessment Report: Climate Change 2007 (AR4) [WWW Document], n.d. URL http://www.ipcc.ch/publications_and_data/ar4/syr/en/contents.html (accessed 4.3.16).

ISO 14040:2006 - Environmental management -- Life cycle assessment -- Principles and framework [WWW Document], n.d. URL https://www.iso.org/standard/37456.html (accessed 3.3.16)

Krzemien, J., 2013. Application of Markal Model Generator in Optimizing Energy Systems. Journal of Sustainable Mining 12, 35–39.

Lallanilla, M., 2015. Greenhouse Gas Emissions: Causes & Sources. URL http://www.livescience.com/37821-greenhouse-gases.html (accessed 8.3.17).

Lapillonne, B., 1980. Long term perspectives of the U.S. energy demand: Application of the MEDEE 2 model to the U.S. Energy 5, 231-257.

LCA Lab, National Metal and Materials Technology Center (MTEC). Thai National Life Cycle Inventory Database [WWW Document]. URL http://thailcidatabase.net/appadmin/db_lci.php (accessed 3.4.17).

Limmeechokchai, B., 2014. Roadmap to Thailand NAMA 2020. URL http://www.thai-german-cooperation.info/download/20141121_eedp_02_Roadmap_Thailand_NAMA_2020.pdf (accessed 22.9.16).

Office of the National Economic and Social Development Board (NESDB). National Accounts of Thailand. URL http://www.nesdb.go.th/nesdb_en/ewt_w3c/main.php?filename=national_account (accessed 4.2.16).

Penphanussak, S., Wongsapai, W., 2008. The Demand for Energy in Manufacturing Sector of Thailand. Technology and Innovation for Sustainable Development Conference (TISD2008), Khon Kaen University, Thailand.

Regression Analysis [WWW Document], n.d. URL http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_multivariable/BS704_Multivariable6.html (accessed 8.3.16).

Selvakkumaran, S., Limmeechokchai, B., Masui, T., Hanaoka, T., Matsuoka, Y., 2015. A quantitative analysis of Low Carbon Society (LCS) measures in Thai industrial sector. Renewable and Sustainable Energy Reviews 43, 178–195.

Su, M., Chen, C., Yang, Z., 2016. Urban energy structure optimization at the sector scale: considering environmental impact based on life cycle assessment. Journal of Cleaner Production, Preventing Smog Crises 112, Part 2, 1464–1474.

Suganthi, L., Samuel, A.A., 2012. Energy models for demand forecasting—A review. Renewable and Sustainable Energy Reviews 16, 1223–1240.

Sykes, A., 1993. An Introduction to Regression Analysis. Coase-Sandor Institute for Law & Economics Working Papers No.20. URL http://chicagounbound.uchicago.edu/law_and_economics/51/ (accessed 8.3.16).

Taylor, P.G., Upham, P., McDowall, W., Christopherson, D., 2014. Energy model, boundary object and societal lens: 35 years of the MARKAL model in the UK. Energy Research & Social Science 4, 32–41.

Office of Natural Resources and Environmental Policy and Planning, 2015. Thailand's First Biennial Update Report (BUR) under the United Nations Framework Convention on Climate Change. URL http://unfccc.int/resource/docs/natc/thabur1.pdf (accessed 8.3.17).

UNFCCC, 2009. Thailand Submits Emission Reduction Plan: NAMAs Gaining Momentum. UNFCCC. URL http://newsroom.unfccc.int/unfccc-newsroom/thailand-submits-nama/ (accessed 25.9.16).

UNFCCC, 2015a. COP 21 Paris France - 2015 Paris Climate Conference [WWW Document], n.d. URL http://www.cop21paris.org/about/cop21 (accessed 25.9.16).

UNFCCC, 2015b. Thailand Submits its Climate Action Plan Ahead of 2015 Paris Agreement [WWW Document]. UNFCCC. URL http://newsroom.unfccc.int/unfccc-newsroom/thailand-submits-its-climate-action-plan-ahead-of-2015-paris-agreement/ (accessed 25.9.16).

Victor, N., Nichols, C., Balash, P., 2014. The impacts of shale gas supply and climate policies on energy security: The U.S. energy system analysis based on MARKAL model. Energy Strategy Reviews, US energy independence: Present and emerging issues 5, 26–41.

What are the major factors affecting natural gas prices? - FAQ - U.S. Energy Information Administration (EIA) [WWW Document], n.d. URL https://www.eia.gov/tools/faqs/faq.php?id=43&t=8 (accessed 8.3.17).

Wisconsin Institutes for Discovery, 2014. Introduction to Optimization. Available Source: http://neos-guide.org/content/optimization-introduction, March 8 2017.

Zhang, G., Lu, J., Gao, Y., 2015. Multi-Level Decision Making Models, Methods and Applications. Intelligent systems reference library 82, Part 2, 25-46.