

**MARKET TREND &
ANALYSIS**

A COMPREHENSIVE SURVEY OF STEEL DEMAND FORECASTING METHODOLOGIES AND THEIR PRACTICAL APPLICATION FOR THE STEEL INDUSTRY

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Global steel demand recovered after the Global Financial Crisis, but it has slowed remarkably since 2014. Unlike in the past, where continuous growth in steel demand accompanied stable economic growth, steel demand and macroeconomic indicators have recently become decoupled because of high uncertainty in the global economy. Consequently, it is difficult to predict steel demand. The steel industry is a base industry that supplies materials to fields including construction, automobiles, shipbuilding, machinery, home appliances, and energy. As steel is an intermediate good used for producing a finished good, it has the characteristics of "derived demand" in which there is a demand for a good or a factor of production driven by demand for an intermediate good. As a result, predicting the demand for steel is more difficult and complex compared to other industries. This article classifies and compiles the methodologies through a comprehensive review of the literature, and then finding clues to enhance the accuracy of steel

demand forecasting.

The approaches, represented in this research, for forecasting steel demand can broadly be classified into the econometric and intensity of use (IU) approaches. In the first section, econometric approaches are divided into the econometric demand model and vector autoregression (VAR). The next section explains the IU approach with specific models and how Roberts (1990, 1996) deduced four decisive factors for steel demand using this model. Other mathematical and hybrid approaches have been tried—the application of both the grey model and algorithm. In addition, this research examines the SWIP (Steel-Weighted Industrial Production) index utilized widely by worldsteel, its member countries, and other steel associations. The last section explains a pragmatic method of POSCO Research Institute (POSRI) for forecasting steel demand to provide practical guidance to the global steel industry, taking Korea's case as an example.

Econometric Approaches

① Econometric Demand Model

An econometric demand model is the most traditional and fundamental econometric approach for predicting steel demand using macroeconomic indicators. Steel is an intermediate good required for producing finished products, so that its demand is a "derived demand" that grows along with the development of the economy and industry. Hence, steel demand is related to higher economic growth, which influences the level of activity in steel-intensive sectors such as capital equipment, construction, and transportation. Therefore, this model widely uses a simple single equation or a simultaneous equation to forecast steel consumption, considering that steel demand is affected by macroeconomic variables including GDP, industrial production, trade structure, and economic volatility.

$$S_t = \alpha \times \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \varepsilon_t$$

where S_t is steel or metal consumption, X_t is real GDP, steel price, and industrial production, etc., all in year t .

Labson *et al.* (1995) used a dynamic, non-spatial, partial-equilibrium world trade model. Steel demand was estimated based on a single linear econometric equation using variables including steel prices, industrial production, and a time trend as a measure of technological change. Pei and Tilton (1999) applied a partial adjustment model to estimate the income elasticity of metal demand in developed and developing countries and added a time trend variable to reflect customer preferences and technological change. Abbott *et al.* (1999) extended a long-run steel demand forecasting models for the purpose of estimating short-run prediction. Long-term forecasting models for empirical analysis used cointegrating regression through such variables as steel consumption, manufacturing production index, foreign exchange rate, steel price, automobile production,

and construction orders. For short-term prediction, error correction models deduced from cointegrating regression were used. McKay *et al.* (2010) forecast steel demand using simultaneous equations by analyzing the variables of investment propensity, urbanization rate, automobile penetration, and technological progress. Yin and Chen (2013) examined the five determinants of steel consumption in nine industries using stock-based models. This method might be meaningful because it is a bottom-up approach for forecasting steel demand.

The econometric demand methodologies are made of simple numerical equations and are easy to explain in practice. Despite such advantages, their innate disadvantages serve as stumbling blocks for prediction. This model requires the use of exogenous forecasts of the explanatory variables. Therefore, this model can better explain past data, but they often fail to forecast future steel demand due to inaccurate prediction of explanatory variables. As long as explanatory variable includes the variable-specific uncertainty such as steel prices and foreign exchange rates, the estimate is not consistent.

② Vector Autoregression (VAR)

The vector autoregression has also been used to forecast steel consumption. This methodology has the merit of avoiding the weakness of econometric demand model that requires forecasts of exogenous variables since VAR assumes all variables in a model are endogenous.

The following are some examples of VAR being used to forecast steel demand. Chen *et al.* (1991) used a vector autoregression model, which consists of real GDP, the consumer price index, money supply, real investment, and steel consumption. Crompton (1999) and Crompton and Wu (2003) used a Bayesian vector auto regression (BVAR) model comprised of multiple variables including steel consumption, real GDP, investment expenditure, and the money supply. The Bayesian approach is relatively appropriate for predicting steel demand because it places proper restrictions on the dynamic coefficients and constant terms

Table 1. Econometric Approaches

		Period	Demand	Variable (X_t)	Country
Economic Demand Model	Labson and Crompton (1993)	1946–1989	Steel, tin, copper, lead, zinc	Income (GDP or GNP), price of a particular metal, and time trend	USA, UK, Japan, OECD countries
	Labson <i>et al.</i> (1995)		Iron ore, steel	Steel price, industrial production, and time trend	Japan, China, North America
	Pei and Tilton (1999)	1963–1992	Aluminum, copper, lead, nickel, tin, zinc	Price of a particular metal and the price of one or more substitutes	20 countries, including USA, Germany, India, France, Indonesia
	Abbott <i>et al.</i> (1999)	1976:1–1988:4	Steel	Industrial economic activity, exchange rate, steel price, motor vehicle production, construction output	UK
	Mckay <i>et al.</i> (2010)	1890–2008	Steel	Investment propensity, urbanization ratio, automobile penetration, and technological progress	14 countries, including Canada and USA
	Yin and Chen (2013)	Vary by variable	Steel	GDP, urbanization rate, saturation level, lifetime of industries, steel intensity	China
Vector Autoregression	Chen <i>et al.</i> (1991)	1952–1988	Steel	Real GDP, consumer price index, money supply, real investment, steel consumption	China
	Crompton (1999)	1970–1997	Steel	Real GDP, investment expenditure, broad money supply	Southeast Asia
	Crompton and Wu (2003)	1952–2000	Steel	Real GDP, consumer price level, real money supply, real investment expenditure, steel consumption	China
	Huh (2011)	1975–2008	Steel	Steel consumption, real GDP, industrial output, fabricated metal product, shipbuilding, cars, home appliances, machinery	Korea

of a conventional VAR model using prior information. The VAR, which is a pure autoregressive model, can create forecasts automatically but the results might not be robust because it does not reflect the exogenous variables. Furthermore, econometrician analyzes such a complicated model, but it is not widely used at the working level.

In the econometric approaches explained so far, important explanatory variables are macroeconomic indicators. However, macroeconomic indicators including GDP are limited in predicting steel demand because they include the development of service, tourism, and financial industries in addition to steel-consuming industries such as construction and manufacturing. Labson *et al.* (1993) found weak evidence to support cointegration relationships, that

is the long-run equilibrium between metals consumption and total income. This means that countries with similar GDPs can have much different steel demand depending on their industrial structures. In addition, the econometric approaches have the weakness of difficulty in reflecting material substitution and technological changes when forecasting long-term steel demand.

The Intensity of Use (IU) Approaches

The intensity of use (IU) approaches, which means the amount of metal consumed per unit of GDP, rose to prominence in the early 1970s. At that time, some OECD member countries observed their steel demand fall while macro-



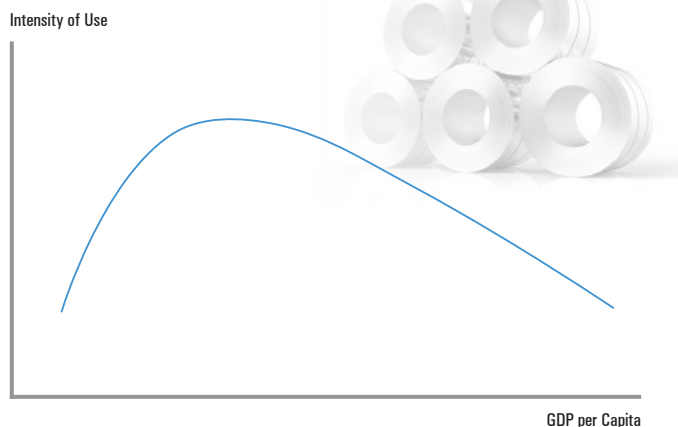
economic indicators grew, econometric approaches then received criticisms. The International Iron and Steel Institute (IISI), currently worldsteel, first suggested the intensity of use hypothesis in 1972. Malenbaum (1973, 1975) formulated the hypothesis regarding intensity of use and suggested an inverted U-shaped relationship between per capita income

and intensity of use (See Figure 1).

This curve shows how the state of economic development affects the level of steel consumed per unit of GDP. As countries at the early stages of economic development grow, their per capita income rises and so does their intensity of use. However, as per capita income continues to grow, industrial structures shift from construction and manufacturing to less material-intensive services, resulting in a decline in both steel consumption and intensity of use.

In the mid-1980s, Roberts (1985), Tilton (1986) and others further developed the IU model. They argued that changes in the material composition of products, caused largely by material substitution and technological change, ultimately affect intensity of use. Tilton (1986) proposed that intensity of use depends on two factors: the product composition of income (PCI) and the material composition of products (MCP).¹ As the economy evolves, there is a shift towards less material-intensive sectors such as services, leading to a decline in the intensity of metal use.²

Figure 1. Intensity of Use Curve



¹ These terms were first used by John Tilton in "Beyond Intensity of Use," *Materials and Society*, Vol 10, 245-250, 1986

² Tilton, J.E., "Changing Trends in Metal Demand and the Decline of Mining and Mineral Processing in North America," *Resources Policy*, Vol 15, No 1, 12-23, 1989

Intensity of Use Technique³

As Radetzki and Tilton (1990, pp. 25~26) show, metal demand can be expressed as

$$D_t = \sum_{i=1}^n a_{it} P_{it}$$

where D_t is the demand for the metal, P_{it} is the output in physical units of the i th good, a_{it} is the amount of the metal consumed in producing one unit of good i , n is the number of goods produced throughout the economy, all in year t .

Letting

$$b_{it} = \frac{P_{it}}{Y_t}$$

where Y_t is national income or gross domestic product (GDP) in year t , and substituting for P_i in equation (1) gives

$$D_t = Y_t \sum_{i=1}^n a_{it} b_{it} \text{ or } IU_t = \frac{D_t}{Y_t} = \sum_{i=1}^n a_{it} b_{it} = f(PCI_{it}, MCP_{it})$$

where IU_t is the intensity of use of the metal, PCI_t is the product composition of income, and MCP_t is the material composition of products, all in year t .

Factors for Steel Consumption Forecast

Roberts (1990, 1996) derived four important determinants of steel consumption using the IU model. As steel is an intermediate product for manufacturing finished products, steel consumption is highly dependent on the product composition of income and the material composition of products. To briefly explain the IU model, the product composition of income (PCI) is a relative proportion of expenditure on a product P to consumers' total income.

$$PCI = \frac{\text{expenditure on } P}{\text{total income}}$$

PCI measures consumer preferences for goods of type P as opposed to all other goods and services available. PCI varies over time due to shifts in the intersectoral structure of the economy.

$$PCI_{it} = \frac{PD_{it} + PI_{it}}{GDP_{it}}$$

where PD_{it} is the domestic production for industry i for consumption and PI_{it} is the imports for industry i , all in year t . Therefore, total consumption for goods of type P is $PCI_{it} \cdot GDP_{it} = PD_{it} + PI_{it}$. With a given GDP , total consumption

³ Tilton J.E. (Ed.), *World Metal Demand: Trends and Prospect*, Resources for the Future, Washington, DC, 1990

depends on predictable PCI .

For the next step, the material composition of product (MCP) means the average quantity of steel used in the production of one unit of a product. This is simply an input-output ratio measuring the relative efficiency of converting steel into final products. The MCP changes over time due to material substitution driven by relative price changes and technological development, such as the production process.

$$MCP_{it} = \frac{S_{it}}{PD_{it} + PX_{it}} = \frac{(input)}{(output)}$$

where S_{it} is the steel consumed by industry i measured in physical units and PX_{it} is the exports for industry i , measured in real value terms, all in year t .

If all products produced in one country were consumed within the nation, steel consumption in year t to industry i can be calculated by multiplying three components (PCI , MCP and GDP) and total steel consumption can be calculated by combining the steel consumption of all industries. In order to reflect the complications of international trade, the model can include the net exports of this product. Taking into account all these relations, steel consumption can be determined as follows:

$$S_{it} = PCI_{it} \times MCP_{it} \times GDP_{it} + MCP_{it} \times PNX_{it}$$

$$S_{it} = \frac{PD_{it} + PI_{it}}{GDP_{it}} \times \frac{S_{it}}{PD_{it} + PX_{it}} \times GDP_{it} + \frac{S_{it}}{PD_{it} + PX_{it}} \times (PX_{it} - PI_{it})$$

where PNX_{it} is net exports: $PNX_{it} = PX_{it} - PI_{it}$.

The aggregate quantity of steel consumed in the entire economy, S_t , in a particular country can be described by

$$S_t = \sum_{i=1}^n S_{it}$$

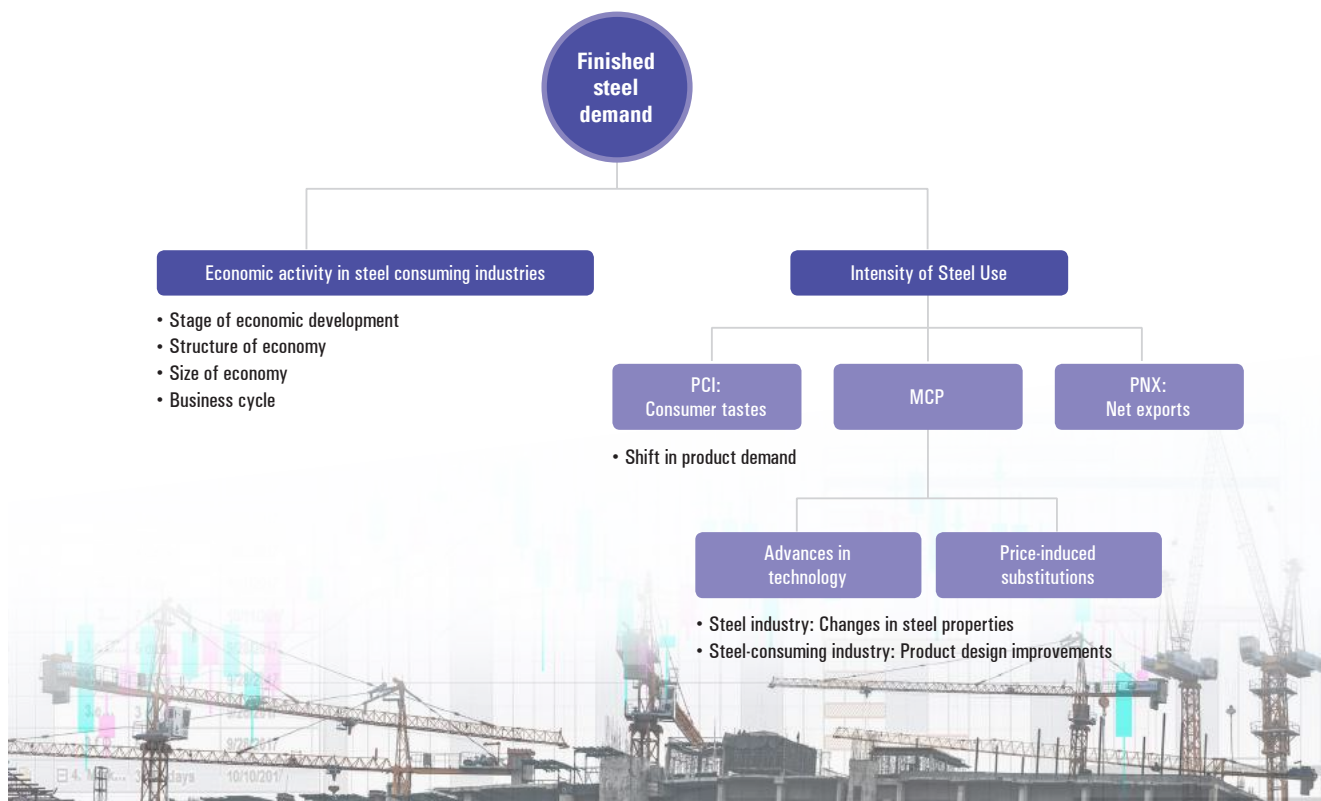
There are four determinants of steel demand: product composition of income (PCI), material composition of product (MCP), income (GDP), and product net exports (PNX). He considers that income (GDP) is an exogenous variable, predicting the MCP and PCI of products is a key to steel demand prediction.

Listed are examples of the IU approach. Roberts (1990) provided the theoretical basis for making metal consumption forecasts and predicted steel demand in the United States. By dividing steel-consuming industries into machinery, transportation equipment, and construction, he was able to reflect the changing proportion of these industries in GDP and steel demand for production by each steel-consuming industry. Roberts (1996) developed a model of metal consumption and predicted world consumption of aluminum, copper, lead, and zinc. But these studies have the weakness of having difficulty in gathering data and explaining causes for technological changes only with time-trend.

Crompton (2000) predicted crude steel consumption in Japan. He studied that steel-consuming industries divided into six categories—machinery, electronic machinery, transportation equipment, other manufacturing, construction, and assembly metal—and deployed time series analysis to overcome the limitations of forecasts by each industry. As a result, the decline in Japanese steel demand after the 1980s can be attributed not only to the stagnation of overall economic growth but also to the changes in the industrial structure. However, Guzman *et al.* (2005) argued that other factors, such as new production technologies, material substitution, and long-term price trends, also influence intensity of use. These do not seem to be linked to per capita income, but rather to time. Rebiasz (2006) analyzed steel consumption in five industries in Poland and calculated it for each sector according to the product composition of income and material composition of product.

The IU approach is a useful concept that attempts to link steel consumption to the technological and structural

Figure 2. Main factors for Steel Consumption Forecasting



Source: POSRI

changes in an economy. Another specific advantage of the IU approach is the disaggregated nature of the analysis in which steel consumption is modeled for different end-use industries. Ghosh (2006) described a positive correlation between steel demand and total income. Evans (2011) and Huh (2011) found a long-term equilibrium between steel demand and total income through an autoregressive fractional integrated moving average (ARFIMA) model. Under the intensity of steel use hypothesis, Warell and Olsson (2009) and Warell (2014) analyzed and verified steel demand and GDP in 61 countries using the ordinary least square (OLS) and a panel regression model. Crompton (2015) applied a fixed-effects panel model for 26 OECD countries and found that per capita steel consumption is concave with respect to per capita GDP. In other words, steel demand growth slows as the economy develops.

Mathematical and Hybrid Approaches

In addition to the two approaches previously mentioned, many researchers have recently been testing other methodologies for forecasting steel demand. This is an attempt to enhance predictability using other models. One case in point is the grey model. For steel demand prediction, Guo (2007) proposed the grey model with historic data of steel products, and found it suitable for predicting demand. Evans (2014) deployed the grey model, which is generally used when the related data is vague and limited. He applied it to predict the intensity of steel use in the UK.

On the other hand, Ma *et al.* (2013) proposed an accurate hybrid model based on the grey model and the PSO (particle swarm optimization) algorithm. Torbat *et al.* (2018) predicted steel demand using a fuzzy ARIMA model

Table 2. The Intensity of Use (IU) Approaches

	Period	Demand	Steel-consuming industry or variable	Country
Roberts (1990)	1963–1983	Steel	Machinery and metal products, transportation equipment, infrastructure	USA
Valdes (1990)	1957–1987	Steel	Traditional manufacturing (assembly metals, transportation equipment, other machinery and equipment)	Australia
Roberts (1996)	1950–1993	Aluminum, copper, lead, zinc	Metal consumption, investment, personal consumption, government expenditures	World
Crompton (2000)	1980–1996	Steel	General machinery, electronic machinery, transportation equipment, other manufacturing, construction, assembly metal	Japan
Guzman <i>et al.</i> (2005)	1960–2000	Copper	Technological change, long-run price trend, real GDP per capita	Japan
Rebiasz (2006)	1974–2003	Steel	General machinery, electronic machinery, automobiles, transportation equipment, construction	Poland
Warell and Olsson (2009)	1970–2004	Steel	Steel consumption, real GDP per capita	61 countries
Warell (2014)	1970–2011	Steel	Steel consumption, real GDP per capita	61 countries
Crompton (2015)	1970–2012	Steel	Steel consumption, real GDP per capita, investment, industrial-sector production, urban population	26 OECD countries

which hybridizes a traditional time series model ARIMA (autoregressive integrated moving average) with PNNs (probabilistic neural networks) used in systems to support decision-making. However, mathematical and hybrid approaches is complex for non-specialists to understand and utilize.

Computational Approaches

The forecasting methodologies for the steel demand are significant theoretically, but cannot be widely applied in practice in the steel industry due to their complexity. They remain simply “pie in the sky” ideas, because of the difficulty

Table 3. Grey and Hybrid Approaches

		Period	Demand	Variable (X_{it})	Country
Grey model	Guo (2007)		Steel	Several categories of steel products	China
	Evans (2014)	1891–2012	Steel	Intensity of steel use	UK
Hybrid model	Ma <i>et al.</i> (2013)	1995–2010	Iron ore	Consumption of domestic raw iron ore, imported ore	China
	Torbat <i>et al.</i> (2018)	1979–2015	Steel	Steel consumption	Iran

SWIP Methodology⁴

A SWIP projection can be made for the use of forecasts for production growth in steel-using industries. How to calculate the SWIP index? First, identify the steel consuming sector, such as construction, mechanical engineering, automotive, domestic appliances, metal goods, shipbuilding, etc., in a country. Second, collect production data on these sectors. Third, estimate the share of each sector in the total steel use. Finally, actual calculation of the SWIP, which is the time series for production in the steel-using industries are indexed at 2000=100

$$SWIP = w_c \cdot C + w_a \cdot A + w_d \cdot D + w_e \cdot E + w_s \cdot S$$

where C =construction, A =automobiles, D =domestic appliances, E =electrical equipment, S =shipbuilding, and w =weights

in making non-specialists understood. Therefore, the computational approaches widely used in practice are examined in this article.

The steel weighted industrial production (SWIP) index is broadly used by worldsteel, its member countries and other steel associations. According to IISI (2005), this methodology can estimate real steel use by reflecting end-user inventories rather than apparent steel use as used in other models. The SWIP methodology can also better reflect the steel consumption structure of an individual country. The SWIP methodology is briefly explained in the above box. The equations for SWIP index seem similar to the regression equation of the economic demand model. The SWIP index designates w (weight) *ex ante* through data unlike the econometric demand model which measures it *ex post*.

The SWIP Index has several advantages. First, the SWIP index computes a weighted average of production indices of steel-consuming industries such as automobiles,

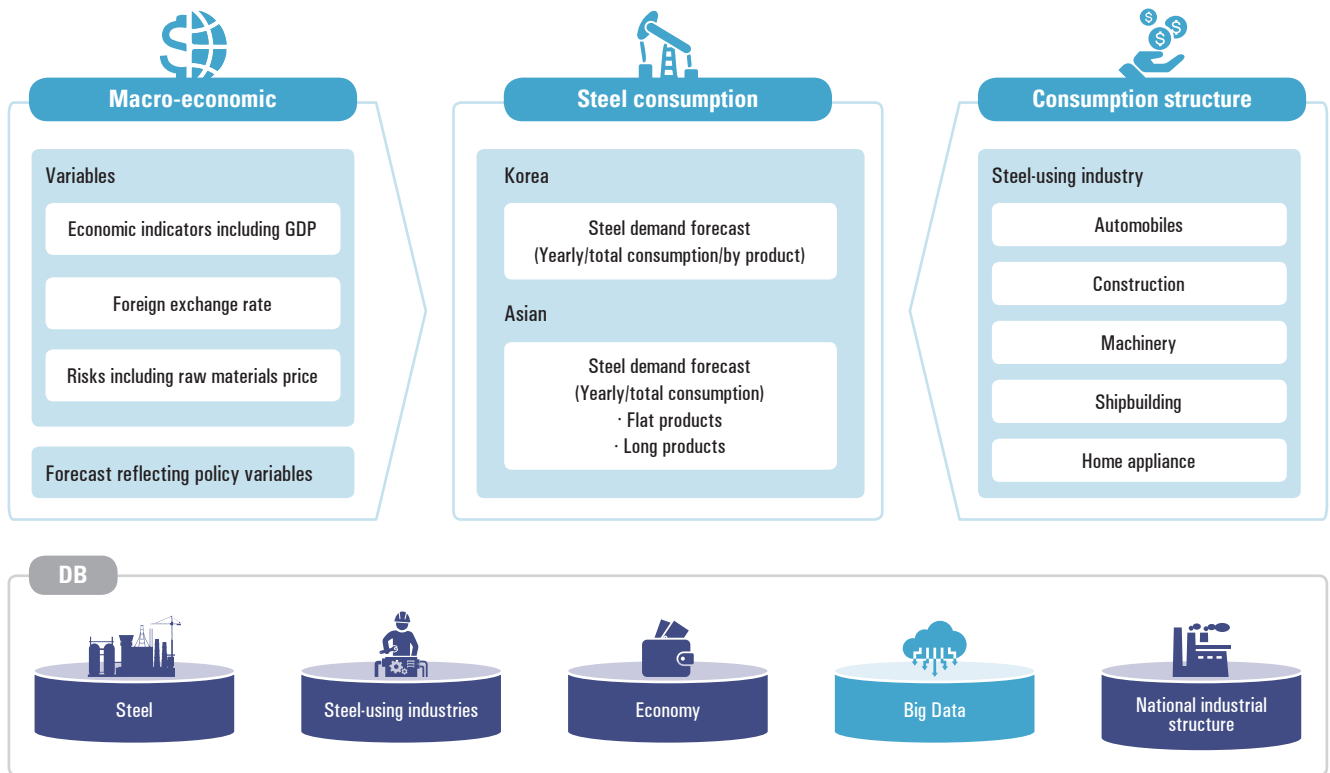
construction, machinery, and shipbuilding. When a specific industry's steel demand is relatively high, its weight increases in the SWIP index. The SWIP index is then able to use additional information for all steel-consuming industries.⁵ Therefore, the SWIP index could realistically reflect changes in steel demand driven by the differences in the industrial structures among countries. Second, apparent steel use is calculated by taking total deliveries of finished steel products and adding net exports because of insufficient information on the inventories of end users. But, the SWIP index estimates real steel use containing inventory changes among end-users. It is highly meaningful that the SWIP index works to address this issue. Finally, it is quite a useful methodology since anyone can use it to intuitively interpret progress and predict steel demand without help from econometricians.

However, the SWIP index has a limitation in whether the estimation is credible, accurate and confidential. For exam-

⁴ International Iron and Steel Institute, Economic Studies Committee (ECON) 2005 Autumn Meeting

⁵ In the case of a econometric demand model, which takes various industries as explanatory variables, they are highly correlated and multicollinearity then occurs. However, the SWIP index is free from this statistical issue.

Figure 3. Steel Demand Prediction System



ple, in the automotive industry, steel consumption differs by type or grade of vehicles, so it is difficult in practice to calculate demand for all subcategories and estimate weight values.

A Suggestion for the Practical Application of Steel Demand Forecasting Methodologies

This article has reviewed several methodologies for forecasting steel demand: traditional econometric and IU approaches and computational methods. At the earliest, most studies predicted steel demand using macroeconomic indicators, but such methods were criticized when steel demand in some advanced countries declined despite economic development. In the 1990s, some studies found that steel demand forecasts are more suitable if using proper indicators

that reflect the structural characteristics of steel-consuming industries. Afterwards, the quality aspect has been factored in, such as mid- to long-term shifts in the industrial structure of the economy and the fluctuating steel consumption structures of industries. To this end, other factors in addition to macroeconomic indicators have been considered: 1) changes in steel intensity of production in each steel consuming industry and 2) changes in the proportion of these industries within GDP.

In Korea, various methods have been deployed to predict mid- to long-range steel demand. To complement the weakness of top-down macro methodologies which directly predict total steel demand, POSRI is concurrently applying a bottom-up micro methodology to predict demand for 16 steel products and summing them to forecast total demand. First, to apply a micro methodology, the industry

Table 4. Estimated Forecast Error by Country (2004 - 2017)

Period	Korea	Japan	China	India	Germany	USA	Turkey	Russia
2004–2012	4.5%	4.8%	5.3%	6.0%	6.1%	9.1%	12.3%	15.1%
2004–2017	4.6%	5.0%	7.3%	5.9%	6.1%	8.8%	8.3%	12.2%

consumption structure is analyzed for all product units. The Korea Iron and Steel Association (KOSA) has been compiling steel shipment statistics by product and industry since 1992, so that steel consumption can be easily identified by these categories. Next, POSRI predicts steel used per one unit output for 16 products, including steel bar, wire rod, section, hot-rolled, cold-rolled, and galvanized steel by the industry weight which is similar to in a SWIP index or IU approach. Finally, total demand is estimated by summing up demand in all products. Unlike in other countries, statistics for Korea are based on finished products and there is no double-counting issue when measuring the demand.

After predicting steel demand in Korea for over a decade using the two methodologies, forecast errors might be reduced significantly. worldsteel (2014) compared steel demand predictability in 11 countries and found that Korea

has the highest level. From 2004 to 2012, the average forecast error rate in these 11 countries was 7.6%, but Korea's rate was the lowest at 4.5%. Recently updated research by POSRI found that Korea's forecast error rate from 2004 to 2017 remained the lowest at 4.6%. This outcome indirectly proves that the micro methodology is highly useful.

The conventional macro methodologies such as econometric demand model and intensity of use can be useful. In addition, computational approaches that reflect long-term changes in steel-consuming industries can enhance the accuracy of prediction and improve the understanding of people in the field. However, for short-run forecasts, Korea's micro methodology should be expanded to other countries to improve the predictive power of steel demand forecasting. This will be meaningful practice for enhancing steel demand prediction. 

Reference

- Abbott, A.J., Lawler, K.A. and Armistead, C., "The UK Demand for Steel," *Applied Economics*, Vol. 31, 1299–1302, 1999
- Chen, D., Clements, K.W., Roberts, E.J., Weber, E.J., "Forecasting steel demand in China," *Resources Policy* 17, 196–210, 1991
- Crompton, P., "Forecasting steel consumption in South-East Asia," *Resources Policy* 25, 111–123, 1999
- Crompton, P., "Future trends in Japanese steel consumption," *Resources Policy* 26, 103–114, 2000
- Crompton, P., Wu, Y., "Bayesian vector autoregression forecasts of Chinese steel consumption," *Journal of Chinese Economic and Business Studies* 1, 205–219, 2003
- Crompton, P., "Explaining variation in steel consumption in the OECD," *Resources Policy* 45, 239–246, 2015
- Evans, M., "Steel consumption and economic activity in the UK: The integration and cointegration debate," *Resources Policy* 36, 97–106, 2011
- Evans, M., "An alternative approach to estimating the parameters of a generalised Grey Verhulst model: An application to steel intensity of use in the UK," *Expert Syst. Appl.* 41, 1236–1244, 2014
- Huh, K.-S., "Steel consumption and economic growth in Korea: Long-

- term and short-term evidence," *Resources Policy* 36, 107–113, 2011
- Gao X.-R., Wang A.-J., "The prediction of China's steel demand based on S-shaped regularity," *Diqiu Xuebao (Acta Geosci. Sin.)*, 31, 645–652, 2010
- Guo, H., "Application of Grey-model in the demand forecast of the steel products," Department of Industrial Engineering and management, Shanghai, Jiaotong University, 2007
- Ghosh, S., "Steel consumption and economic growth: evidence from India," *Resources Policy* 31, 7–11, 2006
- Guzman, J.I., Nishiyama, T., Tilton, J.E., "Trends in the intensity of copper use in Japan since 1960," *Resources Policy* 30(1), 21–27, 2005
- International Iron and Steel Institute, *Projection 85: World Steel Demand*, International Iron and Steel Institute, Brussels, 1972
- International Iron and Steel Institute, "SWIP Methodology", Presentation in Economic Studies Committee (ECON) 2005 Autumn Meeting
- Labson, B.S., Crompton, P.L., "Common trends in economic activity and metals demand: cointegration and the intensity of use debate," *Journal of Environmental Economics and Management* 25, 147–161, 1993
- Labson, S., Gooday, P., Manson, A., "China Steel: China's emerging steel industry and its impact on the world iron ore and steel market," *ABARE Research Report* 95.4, Canberra, 1995
- Malenbaum, W., *Material Requirements in the United States and Abroad in the Year 2000: A Research Project Prepared for the National Commission on Materials Policy*. University of Pennsylvania, Philadelphia, 1973
- Malenbaum, W., *World Demand for Raw Materials in 1985 and 2000*, McGraw-Hill, New York, 1975
- Mckay H., Sheng Y., Song L., "China's metal intensity in comparative perspective," chapter 5 in *China: the next 20 years of reform and development*, Brookings Institution Press, 73–98, 2010
- Pei, F. and Tilton J.E., "Consumer Preferences, Technological Change, and the Short-Run Income Elasticity of Metal Demand," *Resources Policy* 25, 87–109, 1999
- Rebiasz, B., "Polish steel consumption, 1974–2008," *Resources Policy* 31, 37–49, 2006
- Roberts, M. C. *Theory and Practice of the Intensity of Use Method of Mineral Consumption Forecasting*, PhD Dissertation, University of Arizona, Tucson, AZ, 1985
- Roberts, M.C., "Predicting metal consumption: the case of US steel," *Resources Policy* 16 (1), 56–73, 1990
- Roberts, M.C., "Metal use and the world economy," *Resources Policy* 22 (3), 183–196, 1996
- Tilton, J.E., "Beyond intensity of use," *Materials and Society*, Vol 10, 245–250, 1986
- Tilton J.E., "The new view of minerals and economic growth," *Economic Record*, Vol 65, 265–278, 1989
- Tilton, J.E., "Changing trends in metal demand and the decline of mining and mineral processing in North America," *Resources Policy*, Vol 15, No 1, 12–23, 1989
- Tilton J.E. (Ed.), *World Metal Demand: Trends and Prospect*, Resources for the Future, Washington, DC, 1990
- Torbat S., Khashei M., Bijari M., "A hybrid probabilistic fuzzy ARIMA model for consumption forecasting in commodity markets," *Economic Analysis and Policy* 58, 22–31, 2018
- USITC, *Steel Industry Annual Report: on Competitive Conditions in the Steel Industry and Industry Efforts to Adjust and Modernize*, United States International Trade Commission, Washington, DC, 1991
- Warell, L., Olsson, A., "Trends and developments in the intensity of steel use: an econometric analysis," 2009
- Wårell L., "Trends and developments in long-term steel demand—the intensity-of-use hypothesis revisited," *Resources Policy* 39, 134–143, 2014
- Weimin Ma, Xiaoxi Zhu, Miaomiao Wang, "Forecasting iron ore import and consumption of China using grey model optimized by particle swarm optimization algorithm," *Resources Policy* 38, 613–620, 2013
- worldsteel, "Historical Review of Short Range Outlook Forecasts," Presentation in Economic Studies Committee (ECON) 2014 Spring Meeting
- Xiang Yin, Wenying Chen, "Trends and development of steel demand," *Resources Policy* 38, 407–415, 2013