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USING SIMULATION-BASED FORECASTING TO PROJECT SINGAPORE'S FUTURE RESIDENTIAL CONSTRUCTION DEMAND AND IMPACTS ON SUSTAINABILITY

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ABSTRACT

Singapore's 2030 Green Plan aims to advance the nation's sustainable development agenda in alignment with rising global sustainability concerns. Accordingly, construction research is shifting its focus towards the sustainability impacts of the sector's practices. Residential construction, specifically, constitutes the majority of the sector's operations, energy use, and emissions while also having socio-economic impacts on all involved stakeholders. Therefore, this paper investigates demand trends and sustainable performance of the residential construction industry as an essential step towards achieving Singapore's sustainable development goals. As such, this research combines system dynamics modeling and forecasting techniques to (1) forecast the future demand of Singapore's residential sector by modeling the relationships between various influencing factors, and (2) predict the environmental and socio-economic impacts associated with the forecasted increase in demand. The research's value lies in harnessing the power of simulation-based forecasting to aid policy-makers in attaining informed evidence-based decisions regarding the industry's sustainable future.

1 INTRODUCTION

Climate change, among other environmental concerns, and socio-economic issues have intensified the need to comprehensively and thoroughly evaluate the impacts of different industries, specifically the construction industry, on sustainable development and to mitigate future risks. Researchers and practitioners are proposing various profound policies in different countries to reduce and, ultimately, counteract the negative impacts on the environment, economy, and social communities (Idris and Ismail 2011). With such endeavors underway, several governments are yet to be on the right track in terms of restructuring the entire construction sector, and the residential one specifically, for more enduring sustainable outcomes.

Failing to properly manage the construction sector has dire impacts on societies and the environment. Intrinsically, this sector is resource and waste intensive; buildings account for almost 40% of global energy consumption and around 33% of greenhouse gas emissions (Tricoire 2021). In fact, the highest portion of total global energy-related CO_2 emissions recorded, a contribution of 38%, has been attributed to the building sector resulting from constructing and operating buildings (United Nations Environment Programme 2020). Residential buildings alone accounted for 17% of these emissions, indicating its significance in terms of achieving sustainable development goals.

Focusing on Singapore, historical data provided by the *Singapore Department of Statistics* (Singstat 2022) on the value of contracts awarded for public and private residential construction reveals a consistent increase between years 1981 and 2021 from $2.91B to $9.23B (billion Singapore dollars). This trend indicates that the residential sector is rapidly expanding with notable growth peaks in recent years (before the Covid-19 pandemic). This expansion places increasing pressures on the environment and its finite resources, which subsequently impedes any tangible progress resulting from implementing the sustainability plans originally set by Singapore's government and requires continuous revisiting of these strategies based on the current and projected trends.

The pressing matters of sustainability encompass all industries from manufacturing, oil and gas, to transportation, among others. However, given the unique nature and complexity of construction projects, modeling the intricate dynamics of their influencing factors and their associated impacts on all areas of sustainability is key in setting actionable plans and aiding in policy making. Therefore, current advancements in research such as simulation, machine learning (ML), artificial neural networks (ANN) as well as econometric modeling are continuously showcasing their reliability and efficiency in predicting demand trends and lifecycle sustainability performance (Fathi et al. 2020; Ji et al. 2021).

While literature offers a plethora of studies employing either simulation or ML and econometric forecasting techniques to predict energy consumption and environmental performance, the main limitation in previous efforts lies in the missing link that can connect two fundamental matters: the projections of residential construction demand growth and the predictions of the direct impacts such demand projections can have on various aspects of sustainability. In addition, previous research also lacks the robust and holistic approach that can enable it to be successfully realized and established. Therefore, a comprehensive approach for examining the underlying mechanisms and dynamics shaping the demand for Singapore's residential sector and for projecting the long-term impacts such demand trends can have on the sustainable development of the construction industry has yet to be developed.

In attempt to bridge this gap, the overall goal of the present study is to develop a compound approach, referred to as simulation-based forecasting, which combines system dynamics simulation with multiple linear regression (MLR) and ANN to harness the leading benefits of each method and overcome the limitations and drawbacks of applying each one separately. The specific objectives of developing this compound method are three-fold: (1) to provide a thorough analysis of the feedback loops and dynamics between different factors that influence residential construction demand, (2) to forecast future demand trends of the residential construction sector based on historical residential construction data and interactions of these influencing factors, and (3) to predict the effects of the forecasted demand trends on both socio-economic and environmental sustainability indicators. This research aims to specifically address the needs of both policy-makers and researchers as the cooperation between these two parties can bring forth effective and positive results. The practical application of this compound approach is expected to improve the ability of policy-makers to make informed decisions and establish relevant policies based on factual evidence.

2 LITERATURE REVIEW

2.1 Sustainable Development Efforts and the Impact of Construction Industry

Countless research efforts have shifted their focus within the building construction industry to address the issues of sustainability as they seek ways to "green-ify" the industry and curb its impacts. Some studies have been mainly concerned with environmental aspects while others examined the economic portion of sustainability. Social sustainability, on the other hand, has not garnered much attention until very recently as the industry's corporate social responsibility efforts have finally started to embrace diversity, equity, and inclusivity in addition to health and well-being of individuals. This section will review a few notable works addressing sustainability efforts in the construction sector with a focus on the Singaporean market.

Sustainability should be analyzed through a life cycle assessment approach. A study conducted by Kua and Wong (2012) highlighted that greenhouse gas emissions and energy consumptions resulting from building lifecycle stages, specifically the operations/maintenance (O&M) phase should not be neglected, and as such proposed a framework that investigate the entirety of the building lifecycle. While most studies commonly address the O&M phase in their attempt to quantify emissions and energy consumption, it is important to highlight that embodied carbon (carbon emissions produced from the extraction of raw materials, manufacturing, and transporting them to sites) associated with the design and manufacturing stage of projects is in fact the major contributor to environmental sustainability as it accounts for 70–80% of the full lifecycle emissions (Moncaster and Symons 2013).

While most available research studies focus on the environmental aspect of sustainability, Lan et al. (2019) introduced an integrated approach that relies on the net zero energy design concept and on the Triple Bottom Line (TBL) principle. TBL takes into consideration the three pillars of sustainability. In regards to economic sustainability, a study conducted by Dell'Anna and Bottero (2021) highlighted the use of different evaluation methods for measuring the sustainability level of buildings and explored the economic benefits of green labeled buildings with different rating levels. Green labeled building assessment covers four major areas, namely: energy, water efficiency, environmental protection, and indoor air quality among other criteria that might contribute positively to a building's performance. Similarly, a study by Fesselmeyer (2018) showed that buyers understand the value proposed by green and sustainable buildings despite an initial 3% average price increase for a unit in green buildings when compared to a conventional one. This initial investment is counterbalanced by energy savings during operations and maintenance phase and by the positive long-term sustainability impacts such buildings have on societies, owners, and buyers alike.

Regardless of what sustainability areas and project phases are being addressed, an essential driver for sustainable practice is understanding what factors influence sustainability and what hurdles need to be overcome. Accordingly, Yin et al. (2018) solicited the insights and perspectives of Class A Singaporean contractors regarding the procedures and implementation of sustainability practices. The respondents shared their understanding regarding the factors that might increase the adoption of sustainable practices as well as the challenges inhibiting the wide-spread implementation of green practices. Such challenges present various opportunities for policy-makers to steer the industry's direction onto the sustainable path.

2.2 System Dynamics Modeling and Forecasting Methods

System dynamics modeling (SDM) is a simulation approach for understanding the complex feedback loops and interactions of factors within a system over time (Martinez-Moyano and Richardson 2013). Given the complexity of the construction sector, SDM has been widely used by researchers and practitioners to make sense of the dynamics involved. For example, Ozcan-Deniz and Zhu (2016) developed a system dynamics model to aid in selecting a construction method that accounts for sustainability metrics in addition to time and cost criteria. While the majority of sustainability rating systems consider different factors independently of each other, El Hawary and Marzouk (2021) developed a system dynamics model that utilized building sustainability level together with prevailing parameters to model different parameters throughout the building's lifecycle as a measure for sustainability performance.

Forecasting methods have been widely adopted to predict various factors of interest. Bee-Hua (1999) introduced a multiple regression approach for forecasting the Singaporean construction demand. The research presented a comparison between different regression forms to gain precise insights in terms of construction demand. G. Bee-Hua (2000) then further investigated the utilization of a combination of two techniques, neural networks (NNs) and genetic algorithms (GAs), and tested the accuracy of this model using NN as a yardstick. The study concluded that both models generated accurate results.

Combining forecasting methods with sustainability was explored by Marzouk and Azab (2014) to analyze the impacts of construction and demolition waste in terms of environmental, social, and economic impacts. Their objectives included measuring the impact of landfills and uncollected waste on the environment and human health, computing the spared emissions and energy saved from waste recycling, and providing a decision-making tool for waste disposal. The model's output showed that recycling can considerably decrease emissions and global warming potential.

Although these studies have made important strides towards fostering a data-driven approach to improving sustainability in the construction industry, there is limited research that harnesses SDM and forecasting methods together to holistically investigate how projections of the growth in construction demand, specifically the demand for residential building construction, can shape the future trends of the sector's sustainability performance with respect to its environmental as well as socio-economic pillars. Accordingly, the contribution of the present study lies in introducing a simulation-based forecasting approach that uses regression and ANNs to not only predict the demand for residential construction, but also provide an understanding of the sustainability aspect of future scenarios associated with the resulting demand trend. The results of this study can aid policymakers and concerned parties to better fulfil Singapore's 2030 Green Plan and for the decades beyond that.

3 METHODOLOGY

A four-phase framework is developed and implemented as depicted in Figure 1. The first phase includes several steps starting with conducting a literature review on sustainability within Singapore's residential construction sector. The review helps identify (1) a general list of potential factors influencing residential construction demand to be used as a starting point for modeling, and (2) a list of sustainability indicators that are impacted by the forecasted demand trends. Then, the authors of the present study collected historical data from government-based agencies and external entities to identify factors and indicators relevant to developing the simulation-based forecasting model. Based on data availability/access and the quality of data found, the list of factors and indicators was further shortlisted. The final step in phase one was compiling the annual data from 1989 to 2021 as this time period is common for most factors and indicators. This resulted in a 33 point time-series dataset. The forecasting range covers years 2022 to 2050.

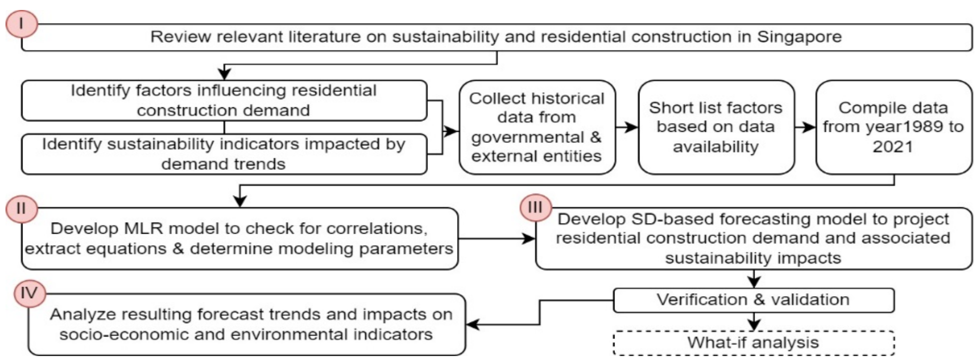

Figure 1: Research framework.

The second phase involves developing an artificial neural network and building a multiple linear regression model. The ANN model serves as a validation of the reliability and predictive robustness of the developed simulation-based forecast model and to cross-check against the reliability of the multiple regression model. The results of the MLR model analysis help define the required equations and modeling parameters for setting up the simulation-based forecasting model. The MLR analysis is primarily used to identify correlations between the dependent variable (residential construction demand) and independent variables (list of influencing factors). MLR is later used again to determine the correlations between the residential construction demand (this then becomes the independent variable after it is forecasted) and the sustainability indicators that are treated as the dependent variables.

The third phase involves developing the system dynamics model where the complex feedback loops between the different influencing factors are modeled to forecast residential construction demand and its impacts on the associated sustainability indicators. The causal loop diagram represents the factors and the links between them that are designated with arrows and signs to indicate the direction of influence and interconnectedness. Based on this causal loop diagram, the stock-flow diagram is formulated and provided with the necessary information (i.e., equations and parameters resulting from the MRM analysis of the previous phase) to represent the residential construction demand–sustainability impact system. The model is then verified, and the system represented by the simulation-based forecasting model is then validated. The validation and verification were performed by comparing the simulated results and the historical data to check how reliable and logical the simulated results are.

The present study, for now, only focuses on modeling the current state of the system based on historical data. Future research can explore and analyze various what-if scenarios where under each scenario, the parameters of the influencing factors are modified, and the resulting forecast trends are assessed. The various possibilities of demand prediction profiles will therefore contribute to changes in sustainability performance of the residential construction sector. Such what-if scenario analysis can be performed by either setting objectives for the desired sustainability indicator values and working backwards, or initially altering input parameters assuming worst- and best-case scenarios. Some ideas on how policy-makers can conduct the what-if scenarios are briefly mentioned in the discussion section. The fourth and final phase of the framework involves analyzing and discussing the results. Analyzing such dynamics within these existing relationships is pivotal in terms of understanding the interplay between influencing factors, demand growth, and the performance of the sector in terms of sustainability measures.

4 DATA COLLECTION

4.1 Factors Influencing Residential Construction Demand

Based on an extensive literature review, multiple factors influencing residential construction demand were identified such as GDP, per capita GDP, resident population, total population, interest rate, property price index (PPI), consumer price index (CPI), under construction contracts, disposable income, household savings, unemployment rate, and vacant residential stock. Then, data related to each of the factors from 1989 to 2021 were explored and extracted from official government agencies and third-party websites (Department of Statistics in Singapore, trading economics, Worldbank organization, statista.com). Based on data availability and the results of the regression analysis that revealed correlation significance, and lack thereof, the following factors were omitted from the model: total population, household savings, under construction contracts, and unemployment rate. The resulting shortlist of 8 influencing factors is presented in Table 1 along with the description of each factor. Note that the GDP per capita was later excluded from the model as it is the equivalent to the GDP divided by resident population, which resulted in forecasting redundancy given the high multi-collinearity detected with the GDP factor. The dependent variable in this study is the demand for residential construction represented by the national-level Gross Fixed Capital Formation (GFCF), which consists of investments in fixed assets by resident producers – deducting disposals – during a given period as measured in millions of Singapore dollars (ESA 2010).

4.2 Sustainability Indicators

This study targets the socio-economic and environmental sustainability pillars. Although the literature highlights a multitude of indicators under each sustainability area, such as housing affordability, accessibility, water consumption, and waste management, the insufficient availability of data due to lack of data or restricted access to datasets has limited the set of sustainability indicators to CO_2 emissions and electric energy consumption for the environmental category, and employment in the residential construction sector as the socio-economic category. The time-series datasets of the CO_2 emissions and electric energy consumption indications are limited to 11 data points (2011-2021), while the employment level is limited to 6 years (2016-2021). Yet, the regression model performance yielded robust results despite the limited data range. Although the list of indicators came down to these three, the main purpose of this work is to demonstrate the power of simulation-based forecasting in projecting a realistic picture of the sector's sustainable performance given the complex interplay of influencing factors.

Table 1: Influencing factors and descriptions.

Factors	Description
1. Gross Domestic Product (GDP)	Measures the monetary value of final goods and services-i.e., those that are bought by the final user-produced in a country in a given period ($M)
2. Resident Population	Indicates the total population residing in Singapore (number)
3. Interest rate (or Prime Lending Rate)	Refers to the interest rate that commercial banks charge their most creditworthy customers (%)
4. Property Price Index (PPI)	Tracks the average change in prices producers receive or pay for goods, housing, and services over time (%)
5. Consumer Price Index (CPI)	Measures the average change over time in prices paid by consumers for a market basket of goods and services (%)
6. Personal Disposable Income (PDI)	Refers to the after-tax income or the amount of money remaining from an income after taxes are deducted ($M)
7. Money Supply (M2)	Includes cash, checking deposits, and near money (saving deposits, small deposits, shares in retail money market mutual funds) ($M)
8. Vacancy (supply)	Represents the number of available housings that are vacant or unoccupied

5 SIMULATION-BASED FORECASTING MODEL DEVELOPMENT

5.1 Multiple Linear Regression (MLR) Model and Artificial Neural Network (ANN)

Multiple linear regression (MLR) modeling was used to predict the values of the dependent variable GFCF (or response variable) based on the values of different independent factors (or predictors) identified earlier as the influencing factors. Then, MLR was used again to predict the sustainability indicator variables (the new response variables) based on the forecasted values of GFCF (the new predictor). MLR modeled these relationships by fitting a linear equation from the historical recorded data while simultaneously considering multiple predictors. The populated regression line and its equation was extracted from the MLR model built in RapidMiner Studio. RapidMiner's linear regression operator was used on the data imported to the software. The goodness of fit was also checked to test how strong the relationship is between the independent variables and the dependent variable. The authors of the present study also tested for the presence of multi-collinearity between the influencing factors. Regression helped in terms of specifying more precisely the relationships between the factors and their effects on each other. The positive/negative correlations between factors fed into the system dynamics model.

Artificial neural network (ANN) was also used and modeled in RapidMiner for forecasting the value of GFCF for future years. ANN models are machine learning models that do not have any restrictions on data distributions. ANN is able to learn and model non-linear relationships; once trained, ANN can then deduce unseen relationships and results can then be generalized (Agrawal 2021). The main purpose of using ANN is for verifying and validating the developed system dynamics simulation-based regression forecasting. Although ANN has a main limitation in requiring complex algorithms to effectively model the complicated relations, it is still used as a benchmark for reliability assessment given its known robustness and reliable forecasting results.

5.2 System Dynamics Model Development

The system dynamics model was developed using Vensim simulation software. The first step in developing the system dynamic model is placing the influencing factors and their compounded effects on one another using arrows as links and specifying the occurring feedback loops. These links formulate the causal loop diagram. The causal loop diagram represents the main feedback mechanisms, which can be either positive to indicate a reinforcing impact, or negative to act as a balancing mechanism. The arrows representing the links are either associated with a positive sign or a negative sign, which are known as the polarities. A positive sign designates factor affects another in the same direction. A negative polarity, however, indicates that a factor has an inverse effect relationship with another factor (i.e., if one factors increases the other decreases based on a given influence magnitude). The next step was to add the stocks and the equations extracted from the MLR model results to generate the stock flow diagram. The important aspect in the model development was including the sustainability indicators and evaluating the effects of the forecasted *GFCF* values on the *CO_2 Emissions*, *Electric Energy Consumption*, and *Employment Level*. The resulting simulation-based forecast model is depicted in Figure 2.

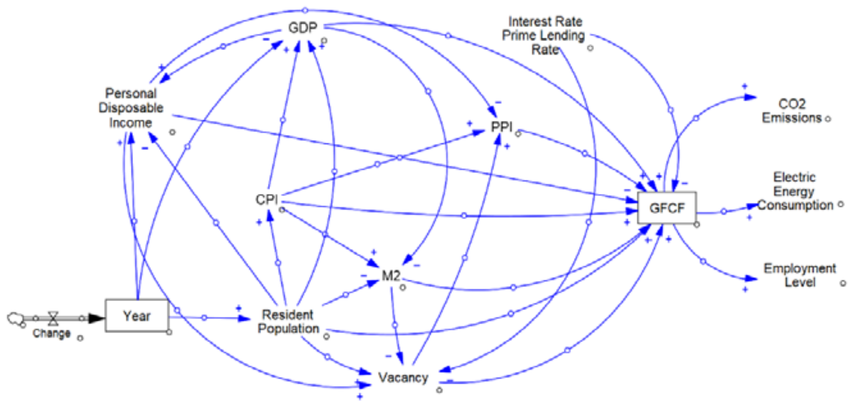

Figure 2: System dynamics simulation-based model.

Taking *Money Supply (M2)* as an example, it connects to *GFCF* with a positive polarity arrow, which means that as *M2* increases in the country and there is more cash flow, the *GFCF* value increases as well as more investment in residential construction is expected as a result. *M2* also connects to the *Vacancy* factor with a negative polarity arrow. This indicates that as more money circulates in the country, firms and individuals have increased purchasing power; hence, their ability to purchase available residential units increases, consequently leading to a decrease in *Vacancy* (or supply). Note that these factors also affect each other indirectly by being intermediate connectors between other factors, where for example *M2* impacts *Vacancy* and *Vacancy* in turn impacts *PPI*, so *M2* indirectly impacts *PPI*. This underscores the complexity of the system represented in this model, where factors are directly and indirectly affecting each other and then affecting the forecast of *GFCF*, which in turn affects the sustainability indicators. Therefore, the only way to understand the real situation holistically is through using system dynamics combined with forecasting techniques. The forecasted *GFCF* values are set to be deterministic instead of probabilistic to simplify the analysis and model development; therefore, future research could explore the stochastic behavior and fit time series into stochastic functions, then examine the model's forecasting behavior to consider probabilistic ranges of data series and projections.

6 RESULTS, ANALYSIS, AND DISCUSSION

6.1 Multiple Linear Regression Model

Table 2 includes a summary of the performance statistics of the regression model analysis for the dependent variable (GFCG) and some of the independent variables (influencing factors) model, and also the dependent variables (sustainability indicators) and what is now the independent variable (GFCG). All variables have a Multiple R (goodness of fit) values that vary between a minimum of 92.2% and a maximum of 99.6%, indicating that the developed MLR model is a proper representation and fits well the observed time series data of the variables. Additionally, the R-squared and adjusted R-squared values vary with a range of 85.0% to 99.1% and 80.7% to 99%, respectively. This indicates that the differences between the observed data and the fitted data from the MLR model are not significant and that the model successfully explains the variations in the dependent variables around their means. The standard error indicates the average distance that the observed values deviate from the regression model where the error values are recorded in the corresponding measurement unit for each variable. For instance, the observed value of the CPI variable deviates by an average of only 4% CPI units from the fitted model, which is considerably low. The main purpose of the MLR is to provide the necessary input equations and coefficients for the system dynamics model to quantitatively depict the interrelationships and polarity of feedback loops between the different influencing factors, the impacts of these factors on the residential construction sector demand (GFCF variable), and the influence of the GFCG demand growth on the sustainability indicators.

Table 2: Performance statistics summary for a sample of the dependent and independent variables.

	Regression Statistics			
Factors	*Multiple R (Goodness of Fit)*	*R-Squared*	*Adjusted R-Squared*	*Standard Error*
Resident Population (Number)	99.1%	98.3%	98.2%	57065
Personal Disposable Income ($M)	99.6%	99.1%	99.0%	1809
CPI (%)	96.4%	92.9%	92.6%	4
GFCF ($M)	98.3%	96.7%	95.6%	1541
CO_2 Emissions(kTons)	94.7%	86.8%	84.2%	136.4
Electric Energy Use (GWh)	92.2%	85.0%	81.3%	232.7
Employment Level (number)	96.7%	93.6%	80.7%	33.5

Equation 1 provides an example of such relations and coefficients between GFCF and the influencing factors resulting from the regression analysis. The + and – signs indicate whether the relationship is directly or inversely proportional. It is important to note that while some of the polarities of these coefficients may not seem logical, the resulting coefficients are collectively regressed (multiple regression) and not assessed individually. Hence, the polarities and weights will differ if analyzed jointly or separately through single regression or multiple regression, respectively.

$$GFCF = -39212.8 + 0.96 * GDP - 0.0075 * Resident\ Population + 31.91 * PPI + 944.68 * CPI - 0.84 * PDI + 0.02098 * M2 + 0.02416 * Vacancy + 627.952 * Interest\ Rate \quad (1)$$

6.2 Simulation-Based Forecasting Output

The coefficient values obtained from the regression models were used as inputs for the SDM to forecast (1) the residential construction demand denoted by the GFCF variable based on the interactions between the influencing factors, and (2) the future trends of the three sustainability indicators pertaining to CO_2 emissions, electric energy consumption, and employment level based on the resulting GFCF forecast. Although in the real-world system many other factors have direct and indirect influences on the selected sustainability indicators, the authors of the present study are limiting the influence on the sustainability indicators to the GFCF factor to maintain simplicity and showcase the model concept.

6.2.1 Residential Construction Demand Projection

Figure 3 illustrates the trend of residential construction demand: the historical trend is designated by the solid line (1986-2021), and the simulation-based forecast trend from 2022 to 2050 is designated by the dashed line. Historically, the residential construction sector experienced peaks and dips impacted by the national and global economic factors, some of which were discussed and modeled here. Most recently, the residential construction sector experienced an extreme dip in fixed capital formation of −54% from a high of 28,708 Million Singaporean Dollars (MSD) in 2013 to as low as 13,321 MSD in 2020 due to the COVID-

19 pandemic. As the economy starts to recover post pandemic, the forecasted results indicate a promising growth for the residential construction sector with GFCF increasing 111% from the low in 2020 to 28,081 MSD by 2030. The projection from year 2030 to 2050 also shows an increase though at a slower rate of 40% to reach 39,273 MSD worth of residential construction demand. Although the modeled projection is linear in nature, it would be interesting for further research to investigate the potential impacts on this forecast trend if other pandemics or force majeure are to occur and whether the Singaporean residential construction market has developed resilience against such unprecedented occurrences.

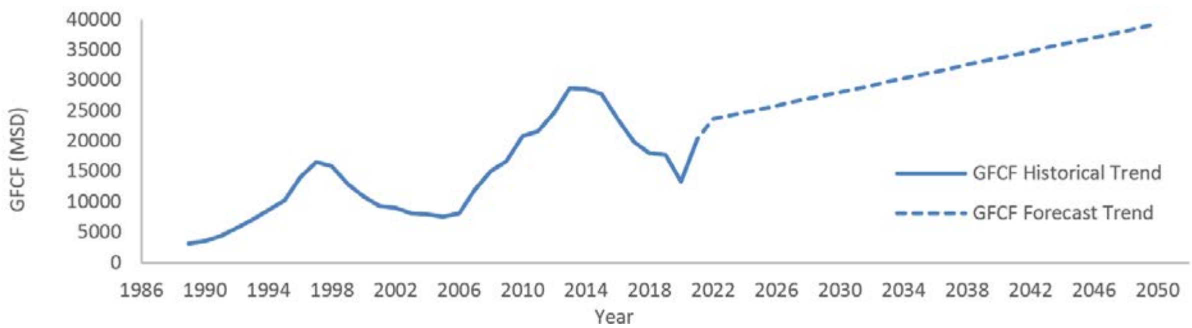

Figure 3: Simulation-based forecast of residential construction demand in Singapore to 2050.

The projected future demand on residential construction is mainly influenced and directly shaped by the complex interactions of the factors modeled. As a hypothetical example, an increase in the nation's monetary supply along with a decrease in the interest rates set by charter banks is expected to support the growth in the residential sector given that these two factors can facilitate constructing, owning, and/or renting residential units. On the other hand, the purchasing power of end users, which also impacts the demand, depends on their disposable income and the property price index, among other factors, at any given time. The higher their disposable income, the higher their purchasing power. However, any increase in the property price index can counter that. While these are very simple examples to picture the feedback loops that exist between all these factors, the system as a whole cannot be verbally simplified. Hence, the importance of forecasting growth trends using system dynamics instead of traditional econometric analysis alone is the key contribution this work is putting forth for the industry. System dynamics simulation-based forecasting can effectively and realistically accommodate the most complex forms of feedback loops and polarities between large sets of variables to predict their influence on other factors of interest. Additionally, the obtained forecast results provide valuable lessons for decision-makers in the residential market to learn from historical events, understand key factors that need to be considered when making important decisions, reflect on the dynamics of the market and acknowledge its heavy reliance on external economic indicators, and embrace advancements that can transform a passive residential construction industry into an agile one.

6.2.2 Impacts on Sustainability Indicators

The impacts of residential growth on the socio-economic indicator, *Employment Level*, and the two environmental indicators, *CO_2 Emissions* and *Electric Energy Consumption*, are plotted in Figures 4 and 5, respectively. Employment level in the residential sector was relatively stable before the pandemic averaging at 35,400 employees. During the peak of the pandemic, employment in the residential sector alone dropped by 5% from 37,840 in the beginning of 2019 to 36,000 (equivalent to 1,000 jobs lost) in 2020. The forecasted trend, however, shows a positive outlook on employment as the construction industry enters the post-pandemic recovery process. With the GFCF projections showing a boom, employment in this sector is naturally bound to follow suit. This is reflected in a 0.63 projected fold increase between 2020 and 2030 (reaching 59,000 jobs) as well as a 0.55 projected fold increase from 2030 to 2050 (reaching 91,000 jobs).

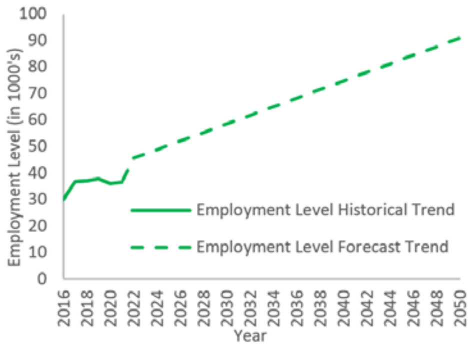

Figure 4: Simulation-based forecast of employment level indicator to 2050.

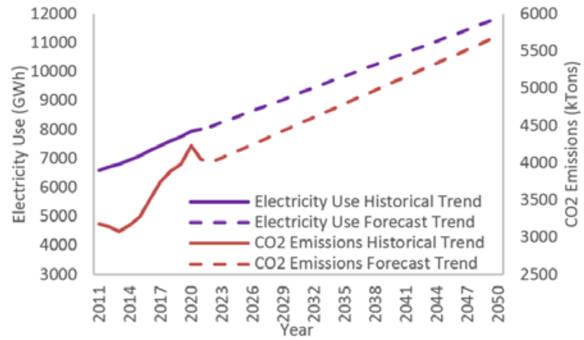

Figure 5: Simulation-based forecast of CO_2 emissions and electric energy use indicators to 2050.

These values seem highly optimistic because the projections are based on a simplified model where the only factor considered to influence the employment level in this study is the residential growth demand. Other factors, already accounted for when projecting GFCF such as the national GDP and money supply, can indirectly influence employment level in a positive or negative manner. For example, if the government invests in developing net-zero energy buildings to achieve its Green Plan targets, the employment levels are expected to positively increase further beyond the natural increase resulting from GFCF's growth. Hence, it is important to keep in mind the simplistic approach adopted here when evaluating the forecasted results of the three sustainability indicators in Figures 4 and 5.

CO_2 emissions and electric energy consumption during the occupancy phase are related because the consumption of electricity yields CO_2 emissions. Other forms of energy, such as natural gas and coal, are also main contributors to CO_2 emissions, but this study is limited to electric energy. The historical trend of CO_2 emissions showed a notable peak during the pandemic with a 9% increase from 3,891 kTons at the end of 2018 to 4,235 kTons in 2020. This in part is a result of the 4% increase in electricity use as well during the same period from 7,616 GWh to almost 8,000 GWh. The increase in consumption and resulting emissions was mainly due to individuals shifting to remote work from commercial spaces to residential units. With the pandemic slowing down and operations in the residential sector gaining momentum again, CO_2 emissions and electricity consumption are both projected to increase as well by 6% and 16%, respectively, between 2020 and 2030 (i.e., 4,500 kTons of CO_2 and 9,185 GWh of electricity consumption). This trend continues to increase through 2050, reaching 5,700 kTons of CO_2 emissions (a 27% increase from 2030) and 11,860 GWh of electricity use (a 29% increase from 2030).

These projections are based on the current state of the system without any interventions to alter it. Although "what-if" scenario analysis is not addressed in the scope of the present study and neither are other contributing factors, it is interesting to at least consider a few points here. With Singapore's 2030 Green Plan in action, and with the construction industry being a major contributor to GDP, emissions, and energy consumption, the industry is in a perfect position to help achieve the plan's sustainable goals. Investing in green construction technology and clean energy can help slow down the forecasted increase in CO_2 emissions despite the increase in GFCF. Ideally, slowing down construction can naturally curb the associated impacts on the ecosystem; however, this will have dire socio-economic impacts such as decreasing employment and GDP. Therefore, the promise of net-zero energy buildings (buildings that consume less energy or an amount equal energy to what they produce) can not only help slow down the upward trend of emissions and non-renewable energy use, but also act as carbon sinks (carbon storage in building materials) to actually decrease circulating emissions. These scenarios are worth modeling through simulation-based forecasting in future research efforts.

6.2.3 Verification and Validation

The results of the verification and validation process are displayed in Figure 6. The trend line for the simulation-based forecast data between 1989 and 2021 is well aligned with the historical data trend line for residential construction demand. The results of the ANN model also closely fit with the historical trend line for the same period. The high resemblance between the results of the simulation model and the historical data shows that (1) the model is an accurate representation of the real-life system (validated), and (2) it is implemented in a correct, consistent, and a complete manner (verified).

The SDM model performance was also compared to the output of the ANN model to test its reliability in forecasting GFCF. The root mean squared error (RMSE) and the mean absolute error (MAE) are 1313 and 1083 respectively for the simulation-based forecast model, whereas they are 1681 and 1203 respectively for the ANN model. These values show that the SDM model actually outperforms ANN in this case as it has the capability of more realistically and simultaneously modeling the intricate feedback loops of the different factors influencing GFCF, and, therefore, more closely represents the historical data collected.

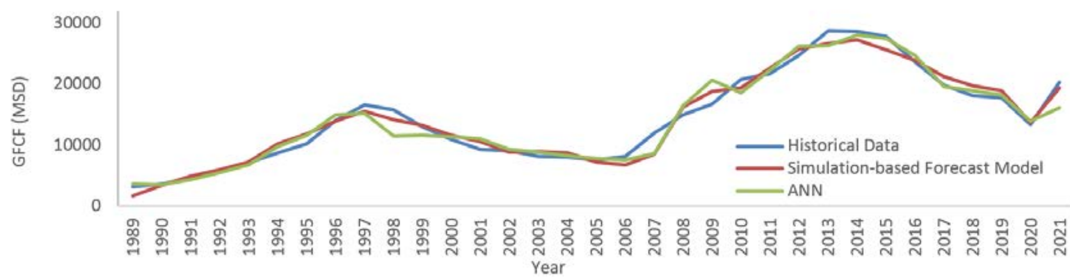

Figure 6: Simulation-based forecast model verification and validation against historical data.

7 CONCLUSION

The present study forecasts the growth in Singapore’s residential construction sector and its impacts on sustainability indicators as Singapore’s 2030 Green Plan is set into action and as the global collective is pushing for sustainable development. Unlike previous research, this work proposes a reliable model that combines the power of system dynamics simulation with forecasting techniques to provide a realistic depiction of the system under investigation. The power of simulation-based forecasting lies in effectively modeling the complex dynamics between a multitude of factors that both directly and indirectly influence residential construction growth patterns, which facilitates the assessment of the impacts of such patterns on not only environmental sustainability but also socio-economic indicators. This model also allows policymakers to investigate what-if scenarios in a virtual environment before drafting and passing on certain policies that are needed to alter the residential construction sector into a sustainable hub. Experimenting with the system, for example, can be done by altering feedback loops between influencing factors, changing the weights of their influences, adding alternatives such as clean technology and energy, and placing tentative policies as variables. Nonetheless, data availability, including the number of data points, was a key limitation of the study affecting the number of factors and indicators modeled and the choice of the forecasting techniques. Although the presented work is just the tip of the iceberg, it does have the potential to be a game changer in the context of this volatile and complex construction market.

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