PROCEEDING

ICONETSI

International Conference on Engineering and Information Technology for Sustainable Industry **2022**

21 – 22 September 2022

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MESSAGE FROM RECTOR

The Covid-19 pandemic has substantially posed challenges to the world of a magnitude that we did not specifically anticipate before. On the other hand, it has also opened up new possibilities for technology and innovation in our daily lives and workplaces. In the post-pandemic period that we are experiencing at present, technology and innovation play even bigger roles to improve effectiveness and sufficiency for sustainability on our planet with a particular emphasis on human wellbeing. Despite the size of the task and the current unpredictable path of the world, the transformation to a sustainable future is not impossible because we have the knowledge, tools, and capacity.

Therefore, bringing forward the theme "Fostering Innovation and Technology for the Sustainability of the Post-Pandemic Society", our International Conference on Innovation, Entrepreneurship, and Technology (ICONIET) this year serve as a forum where academics, researchers, industry practitioners, and government officials discuss the significance of innovation, research, and technology in presenting potential solutions for establishing a sustainable future for people and the environment.

For the last seven years, Swiss German University has been regularly conducting the ICONIET as a token of contribution to quality research and education. This year, the ICONIET consists of two sub-conferences, namely "International Conference on Engineering and Information Technology for Sustainable Industry 2022 (ICONETSI)" on 21-22 September 2022 and "International Conference on Biomedical and Pharmaceutical Sciences and Technology (ICOBIPST) on 1 and 2 October 2022.

I'd like to take this opportunity to welcome all honourable speakers, presenters, and participants from Indonesia and other countries. I wish to express my gratitude to the Minister of Communication & Information of the Republic of Indonesia, Mr. Johny G Plate for his tremendous support in this conference. I'd like to further thank the Ministry of Research and Technology as well as the National Research & Innovation Agency (BRIN) for their continuous support of our research. Our deep appreciation also goes to the University of Brawijaya Faculty of Medicine, the co-host of the first ICOBIPST at this conference. Last but surely not the least, I'd like to thank the Committee of ICONIET 2022, including the committee of ICONETSI and ICOBIPST 2022, who have put their utmost efforts into organizing these events.

I wish all participants to experience insightful and productive times in this conference. I hope this event will give invaluable new ideas and potential solutions for establishing a sustainable future in these challenging times. We look forward to seeing all of you at the ICONIET 2022.

Respectfully yours,

Dr. rer. nat. Filiana Santoso
Rector of Swiss German University

MESSAGE FROM CONFERENCE CHAIR

On behalf of the organizing committee, it is my pleasure and privilege to welcome you to the 2nd International Conference on Engineering and Information Technology for Sustainable Industry (ICONETSI 2022).

Under the theme of "Innovation and Technology for Resilient and Sustainable Industry", the conference offers a platform for scholars, engineers, scientists, practitioners, and students from universities and industries around the world to perform knowledge exchanges about research and development activities.

This conference features a rich program, including a keynote speech delivered by honourable Minister of Communication and Informatics Republic of Indonesia - Mr. Johnny G. Plate, and also keynote speech from Dr. R. Herdian – Deputy for Utilization of Research and Innovation BRIN. In the plenary session, the speeches will be delivered by Dr. Nuki Agya Utama - Executive Director at ASEAN Center for Energy and Assoc. Prof. Dr. Waseem Haider from Central Michigan University, while in the parallel session, we are delighted to have Prof. Dr. Dominik Aufderheide from Fachhochschule Südwestfalen, Germany, Prof. Dr.-Ing. Matthias Schirmer from Ernst-Abbe-Hochschule Jena, Germany, Prof. Dr. Wahyudi Sutopo from Lithium Battery Research and Technology Centre, Universitas Sebelas Maret, Surakarta, Indonesia, Dr. Selvakumar Ramachandran from Kerckhoffs Ltd, United Kingdom, and Kholis Abdurachim Audah, Ph.D from Swiss German University; Indonesia

All accepted and presented papers in this conference will have the opportunities to be published in ACM International Conference Proceeding Series and indexed by Scopus. The conference has received 92 submitted papers from Japan, France, Taiwan, Peru, Saudi Arabia, and Indonesia whereby 68 papers have been accepted by the committee for presentation and to be included in the proceedings. Each submission is evaluated by at least three reviewers in a blind review procedure to guarantee the high quality of the articles. Additionally, we thoroughly review each submission's writing style in accordance with the conference proceedings template and the similarity rating to prevent plagiarism.

I would like to express my highest gratitude to every one of the organizing committee members, the reviewers, the moderators, the session chairs, the collaboration partners, the volunteers, and the sponsors for their amazing efforts in making this conference successful.

Thank you for being here with us. We value your presence at this conference. Enjoy the conference!

Warm Regards,
Dr. Eng. Aditya Tirta Pratama
ICONETSI 2022 General Chair

Keynote Speaker

Development and Characterization of Thin Film Metallic Glasses for Biomedical Applications

Assoc. Prof. Dr. Waseem Haider
Central Michigan University, USA

Abstract:

Novel thin film metallic glasses are synthesized for advanced biomedical applications using magnetron co-sputtering. The formation and properties of metallic glasses are optimized via compositional variations using power densities of sputtering gun. These films are subsequently characterized for surface, electrochemical and mechanical properties. The structural characterizations are done using Glancing-angle X-Ray Diffraction, Transmission Electron Microscopy and X-Ray Photoelectron Spectroscopy. Moreover, the electrochemical characterizations are carried out using Potentiodynamic polarization and Impedance spectroscopy. This research offers a new way of synthesizing metallic glasses for advanced applications.

Short Biography:

Dr. Waseem Haider is a tenured associate professor at School of Engineering and Technology, Central Michigan University, USA. He earned his PhD in Mechanical Engineering from Florida International University in 2010. He got a post-doctoral fellowship in materials science and engineering at Pennsylvania State University. Afterwards, he joined orthopedic research labs as a research scientist at State University of New York. Soon after that, he joined University of Texas as tenure track assistant professor where he served for three years. Dr. Haider's research focuses on Materials Science and Biomedical Engineering with special emphasis on Biomedical Materials Surface Chemistry, Electrochemistry, Bulk Metallic Glasses, and Nanomaterials. His research is supported by National Science Foundation and Department of Defense.

Keynote Speaker

Strategic Energy Transition for ASEAN

Dr. Nuki Agya Utama
Executive Director of the ASEAN Centre for Energy (ACE)

Abstract:

The ASEAN economic growth has been one of the fastest in the world, which needs to be fueled by energy. The 6th ASEAN Energy Outlook (AEO6) projected that the primary energy supply in 2040 will be 2.1 times higher than the 2017 level. Still dominated by fossil fuels, ASEAN will become a net importer of gas starting in 2025 and coal starting in 2035—assuming no significant exploration. With the volatility of fossil fuel markets, energy security needs to be addressed in the region's energy transition.

The region, through the ASEAN Plan of Action for Energy Cooperation (APAEC), put energy security as one of its four pillars, along with accessibility, affordability, and sustainability. Within that are the regional energy targets, achieving 23% of RE share in TPES, 35% of RE in installed power capacity, and 32% energy intensity reduction by 2025. Nevertheless, a just energy transition would require ASEAN to secure its energy supply by optimizing the energy mix from the indigenous primary energy sources. The importance of geopolitics, diversification of energy sources, and improvement of capacity and technology are seen to be key strategies.

Short Biography:

Dr. Nuki Agya Utama is appointed as the Executive Director of the ASEAN Centre for Energy (ACE) and reporting directly to an International organisation under ASEAN entities and reporting to Governing Council consist of ministries energy in ASEAN member states. He is currently an advisory board member of Asia Pacific Energy Research Centre (APERC) and World Economic Forum (WEF) Global Future Councils.

Dr. Nuki Agya Utama has academics and research background as Post-Doctorate in Graduate School Energy Science Kyoto University for energy scenario planning in South East Asia. Holding PhD, with research on Life Cycle Energy Analysis from Joint Graduate School of Energy and Environment, the University of Technology King Mongkut (KMUTT), Thailand.

Prior to assuming his position in ACE, he worked as a director various local companies and as a consultant in a well-known international Institutions. In his early career, he worked as a consultant in UNDP and UNEP, working on energy and environment-related issues. He also serves as an invited lecture in Diponegoro University as well as editor and reviewer in a various international journal.

Invited Speaker

The Indonesian Natural Products Library: an Indonesian Natural Products Database for Drug Discovery

Kholis Abdurachim Audah, PhD.
Director of Academic Research and Community Service
Swiss German University

Abstract:

Indonesia is one of megabiodiverse countries in the world which has abundant natural resources both on land and marine. Natural resources have been utilized as the resources for traditional medicines that have been practices for generations. The term natural product refers to natural resource, mainly biota, that has medicinal benefits. Various researches on natural products have been vigorously conducted in Indonesia, especially since 2015 when the Indonesian government launched a National Research Plan (2015-2044). In this plan, research on natural products had become country's top research priority. Despite this positive atmosphere for natural products researches, researches conducted are still scattered and lack of coordination, communication or collaboration among researchers and or institutions. One of the problems to this condition is due to the absence of a common database platform for scientist to display their works. The platform can be used as the source of information so that people can follow and learn about different research that have been conducted, on what areas and the stage of the researches.

The Indonesian Natural Products Library (INPL) is developed to solve this problem to ensure that all researches utilizing Indonesian biodiversity, particularly in the area of drug discovery or pharmaceuticals, are more effectively done. As the source of information, INPL will enable the synchronizing and synergizing Indonesia's natural products-based research so that unnecessary activities such as overlapping and discontinuation of researches can be avoided. In addition, INPL will also be useful for finding alternatives for other areas such as food and energy sources.

Short Biography:

Dr. Audah earned his PhD in Biochemistry from Auburn University, USA (2007). He did his Postdoctoral Research at Yale University School of Medicine, Section of Infectious Diseases (2009). Dr. Kholis Audah earned his Bachelor Degree in Chemistry/

Biochemistry from Bogor Agricultural University, Indonesia (1996) and a Master Degree in Molecular Biology from University of Malaya, Malaysia (2000). Currently, he serves as the Director of Research and Community Services and Senior Lecturer at Department

of Biomedical Engineering, Swiss German University (SGU), Tangerang (2015-present). Before joining SGU, he held different positions at different institutions in Indonesia, Saudi Arabia and USA.

His current researches focus on Drug Discovery on antibacterial and anticancer from Indonesian natural products as well as synthetic compounds and Telemedicine. His project in Development of Mangrove Extract Library for Drug Discovery and Development of Microscope Scanner for Telepathology were funded by the Ministry of Research and Higher Education, Republic of Indonesia. He also obtained international and industrial funding as well as Awards from various institutions. He is the inventor of the Indonesian Natural Products Library (INPL) and the Citizen Medicine (CitMed) databases.

Dr. Audah is actively involved in different scientific organizations and scientific activities as Editor in Chief, Editorial Board Members and Reviewer in several national and international journals. Before joining SGU, Dr Audah was the Head of Biochemistry Departments and Laboratory and Assistant Professor at the College of Medicine, University of Hail, Hail, Saudi Arabia. He was also the Lead Scientist (Research and Laboratory) for the establishment of the Indonesia Medical Education and Research Institute (IMERI), Faculty of Medicine, University of Indonesia. He earned some professional certifications such as Good Clinical Practice from the Indonesian Association for the Study of Medicinal, Certified Reviewer from Kemenristekdikti and ISO 17024 and Certified Biosafety Level 2 and Radioisotope handling, Yale University.

Invited Speaker

Therapeutic Potential of Organic Fermented Soybean Extract Against Lead (Pb)-Induced Zebrafish Via NMR Metabolomics Approach

Assoc. Prof. Dr. Intan Safinar Ismail
Dean of Faculty of Science, University of Putra Malaysia

Abstract:

Lead (Pb), even in small quantity, is harmful to multiple body systems. Dimercaptosuccinic acid (DMSA), one of the chelators that used to treat Pb toxicity also gives various negative side effects. Tempeh, one of the fermented soybeans is known having high antioxidant effect which might potentially be useful in alleviation of Pb toxicity. Organic foods are sold with a higher price than the non-organics as the organics are claimed to be better in terms of health benefits. However, the difference in the phytochemical content between organic and non-organic soybeans that related to their quali-ties is not well explored. Thus, this study assessed the therapeutic potential of organic fermented soybean extracts (FSE) against Pb toxicity using a zebrafish model. Non-targeted NMR metabolomics was used to study the difference in the chemical profiles between non-organic and organic soy-beans (Glycine max [L.] Merr.), and the metabolite changes after fermentation using Rhizopus oligosporus. The Pb and FSE concentrations were preliminary investigated before proceeding further with the therapeutic study of FSE against Pb toxicity in zebrafish model. All zebrafish samples were evaluated using NMR metabolomics with additional support behavioral test and transmission electron microscope (TEM) analysis. Zebrafish that exposed to 50 mg/L FSE significantly changed four metabolites namely glucose, isoleucine, sn-glycero-3-phosphocholine, and glutamine. Preliminarily study of Pb inducement significantly altered the behavior of zebrafish and non-lethal 5 mg/L Pb concentration which altered the metabolite profiles of zebrafish are selected for further investigation. In the therapeutic study, citrulline was significantly upregulated only in Pb-induced group without any treatment.

FSE-treated (50mg/L) Pb-induced zebrafish might potentially retrieve the effect of Pb toxicity by significantly upregulated four key differential metabolites (glutamine, glutamate, glutathione, and taurine). Even though the treatment groups (FSE and DMSA) did not normalize to control, yet they differ from Pb-induced group without any treatment. These results presumed that FSE has potential to ameliorate the Pb poisoning effect in this fish model.

Short Biography:

Associate Professor Dr. Intan Safinar Ismail completed her PhD and post-doctoral studies at Okayama University and Hoshi Medical University, Japan. She joined Universiti Putra Malaysia (UPM) in 2005 and became the Head of Laboratory of Natural Products at the Institute of Bioscience in 2011 until 2017. She is now the Head of Chemistry Department, Faculty of Science. Within the period of her affliation to the Universiti Putra Malaysia, she has published more than 190 papers in reputed journals and presentations at conferences as speakers including keynote and invited at international meetings. She led 14 research projects and leading 2 at the moment and more than 5 as a co-worker. Seven Ph.D. and 13 MSc students have graduated under her supervision, with 3 Ph.D. and 1 MSc students are currently enrolling. She co-supervised more than 50 postgraduates. She is editor for a few journals including Journal of Natural Medicines (Springer), review editor for Marine Biotechnology (Frontiers) and Specialty Section of Natural Products (Frontiers).

Invited Speaker

Current Challenges of the Energy Market - Between Net Zero Scenario and Security of Energy Supply

Prof. Dr.-Ing Matthias Schirmer
EAH Jena, Germany

Abstract:

With the adoption of the climate targets, the European energy market is facing a fundamental transformation. Fossil energy sources must be replaced by low-emission, renewable types of energy production. In the field of electricity generation, some successes have been achieved in the last decade. The share of renewable energies in electricity generation in the EU-27 was 22% last year. Greenhouse gas emissions have been reduced by 32% since 1990. These successes should not obscure the challenges that lie ahead, especially in the heat supply and mobility sectors. The war in Ukraine has further aggravated this situation. In addition to the goal of reducing emissions, the main concern now is to secure the energy supply. This raises the question of how to reduce dependence on Russian oil and gas supplies. Furthermore, how can we deal with energy prices, which have risen drastically in some cases? In the following, the current situation of the European energy market will be analyzed, and possible solutions discussed.

Short Biography:

Prof. Dr.-Ing. Matthias Schirmer is Professor for Energy and Environment (W2) at the Faculty of Industrial Engineering at the University of Applied Science Jena, Germany. He is currently a Vice- Dean of the Faculty Industrial Engineering and Director of the post graduate study program “Environmental and Geo resource Management”. Prof. Dr.-Ing. Matthias Schirmer has academics and research background as PhD thesis (Dr.-Ing.) Dresden University of Technology, with research on Waste characterization and energy generation by waste and biomass, and also Energy systems modelling and simulation. He has experienced in various teaching, research and project stays in Portugal, Greece, Peru, Chile, Ecuador, Indonesia, Vietnam, Thailand, India, Namibia and South Africa.

Invited Speaker:

Emerging Technologies for ALL

Dr. Selvakumar Ramachandran
Kerckhoffs Ltd, UK

Abstract:

In human history 'technological' revolutions brought in a greater level of playing field for society. It has not just created opportunities and created wealth, but it strengthened the connectivity, human bonding even stronger. Given the advancement in telecommunications, particularly 5G combined with VR/AR, innovators and researchers believe that it can bring a greater level of inclusion and accessibility in several domains. We, at Kerckhoffs Ltd, creating Eyemmersive - an inclusive VR-based tourism platform for all, connecting VR-content creators to the people who want to have alternative platform to have parallel tourism and a tool to plan before they travel. Dr Ramachandran will speak about VR in accessible tourism and how it can support inclusion in other domains

Short Biography:

Dr Selvakumar Ramachandran is the CEO of UK based software R & D company Kerckhoffs Ltd. Dr Ramachandran is one of the pioneers in the field of emerging technologies and a flag bearer promoting technology for all. Dr Ramachandran earned his PhD from University of Rome – Tor Vergata, Italy and he received his MSc degree from Blekinge Tekniska Hogskola, Sweden. Dr Ramachandran has for 20+ years of experience in the field of computer science, published several papers and was a recipient of Google Scholar award in the year 2012.

Invited Speaker:

Intelligent Systems and Strategies for a Sustainable Cement Manufacturing

Prof. Dr.-Ing. Dominik Aufderheide
Fachhochschule Südwestfalen, Germany

Abstract:

Approximately 4-8% of the total global emissions of carbon dioxide (CO2) are caused by the usage of concrete. Here, especially the process of cement manufacturing is very energy intensive and the usage of large amounts of fossil fuels is typically involved within the main clinkering process. Therefore, the usage of Alternative Fuel Resources (AFR) has become a main technique towards a greener cement production. Due to the volatile combustion characteristics of those bulk materials, the process control has become a challenge for plant operators. This talk provides an overview of recent methodologies for the optimization of cement plants in order to reduce the associated environmental impact. In this context, especially intelligent system architectures and model-based optimization techniques are introduced and discussed. Furthermore, the incorporation of sensors and vison-based approaches for a model-based process optimization are evaluated.

Short Biography:

Prof. Dr. Dominik Aufderheide is a full professor for industrially metrology at the Faculty of Electrical Engineering at the South Westphalia University of Applied Sciences. His research interests are intelligent sensor systems, computer vision, model-based design and optimisation techniques and energy optimization. Before he returned to academia in 2020, he worked for several years as the head of automation and research at the Di Matteo Group in Beckum, Germany, where he led several development and research projects related to the process optimization in energy-intensive industries, such as cement and steel production or in electrical power plants. He graduated in 2014 from the University of Bolton, U.K. as a Ph.D. with a dissertation about the self-acting 3D scene reconstruction based on a novel sensor-fusion approach. At the same university, he received his Master's degree in Electronic Systems and Engineering Management with Distinction in 2009. Before that he studied Electrical Engineering and Industrial Informatics at the South Westphalia University of Applied Sciences in Soest, Germany.

Invited Speaker 4:

Accelerating A Commercialization of The Innovation Technology Using Early Supply Chain and Standardization:

A Case Study of Energy Storage Technology

Prof. Dr. Ir. Wahyudi Sutopo, ST., M.Si, IPM.
Universitas Sebelas Maret

Abstract:

In most cases, many technology products resulting from research happened to fail to be launched to the market due to the valley of death. This obstacle usually occurs in the transition process between technology development and technology commercialization. Hence, critical action is needed to accelerate the technology commercialization to ensure the commercialization potency of research output does not fall into the valley of death. The innovation of the Electric Motorcycle Swap Battery (EMSB) technology encourages the formation of a new ecosystem at the early of the supply chain, including technopreneurs and startups from manufacturers, suppliers, and distributors for commercialization. Swappable Batteries (SB), Electric Motorcycle (EM), and Battery Swap/Charging Station (BSCS) are key components of EMSB that have attracted the attention of supply chain players and government to find a thriving solution to enable faster adoption and diffusion of EMSB in Indonesia. Previously, the Center of Excellence for Electrical Energy Storage Technology, Universitas Sebelas Maret (or CoE-EEST UNS) has developed SB, EM, and BSCS prototypes with limited systems to operate the EMSB. However, to transfer technological innovations and/or facilitate operations of the EMSB on a large scale, there are various challenges and problems with products, processes, innovations, and businesses that are required to be solved. There are five interventions/models that were proposed by CoE-EEST UNS, namely circular business for EMSB, innovation diffusion and adoption, technology readiness and economic benefits prediction, location-allocation for smart charging, and Internet of Things based decision support system for distributing EMSB, and the technical requirements for interoperable of EMSB. The interventions/models are seen as alternatives to accelerate the downstream of EMSB technology innovation, and then maximize the economic benefits of a green economy in Indonesia

Short Biography:

Wahyudi Sutopo is a professor in industrial engineering and Head of Industrial Engineering and Techno-Economics Research Group, Department of Industrial Engineering, Universitas Sebelas Maret (UNS), Surakarta, Indonesia. He is also as researcher for center of excellence for electrical energy storage technology (CoE-EEST), the president of the industrial engineering and operations management (IEOM) society for Indonesia's professional chapter, and Director, IEOM Asia Pacific Operation. His

educational background is the profession of engineer from UNS (2018); Doctor and Bachelor in industrial engineering from Institut Teknologi Bandung (2011 & 1999); and master of management science from Universitas Indonesia (2004). His research interests include supply chain engineering, engineering economy & cost analysis, and technology innovation & commercialization.

Dr Sutopo has completed research projects with more than 45 grants and carried out research projects funded by Institution of Research and Community Services - UNS, Ministry of Research and Technology / National Agency for Research and Technology, Indonesia Endowment Fund for Educational (LPDP), PT Pertamina (Persero), PT Toyota Motor Manufacturing Indonesia, and various other companies. He has written 4 text books and 7-chapter books and made 5 intellectual property rights (IPR) in the form of copyrights, and 3 patents. He has initiated to commercialize research outputs of UCE-EEST UNS related to energy storage technology and electric vehicle conversion through start-ups where he is one of the founders, namely PT Batex Energi Mandiri and PT. Ekoelektrik Konversi Mandiri. Dr Sutopo has published articles over 185 documents indexed by scopus with H-index 13. His email address is wahyudisutopo@staff.uns.ac.id.

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by Muhammad Hendra

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Optimization of Production Planning Using Goal Programming and Inventory Control Based On Demand Forecasting Using Neural Networks On CV Bahyu Perkasa

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ABSTRACT

CV Bahyu Perkasa is a company engaged in the concrete construction industry. One of the products produced is paving block. The number of fluctuating demands makes the company decide to stockpile products and procure raw materials regularly to meet consumer demand. This was Born in over-production and overstock. Therefore, a consumer demand forecasting method is needed so that it can minimize production costs and maximize profits. In addition, inventory control methods are needed to reduce storage costs and ordering costs for raw materials. The method used for demand forecasting is an artificial neural network with an MSE error accuracy rate of 0.017769. Forecasting results are used to optimize production planning using goal programming and inventory control planning using MRP. The results of the goal programming optimization model with priority determination produce an optimal solution in fulfilling consumer demand and minimizing production costs of Rp. 99,205,774.00.

CCS CONCEPTS

• Applied Computing ~ Operations Research ~ Industry and Manufacturing • Applied Computing ~ Operations Research ~ Forecasting

KEYWORDS

Optimization, Production Planning, Forecasting, Artificial Neural Network, Goal Programming

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1 Introduction

CV Bayu Perkasa is a company engaged in concrete construction. The production process applied by the company uses two methods: make to stock and make to order. Products made with make-to-stock are products with a high enough demand, while products made with make-to-order are products with unique specifications from consumers, and the number of requests is low [1].

The paving block is one of CV Bayu Perkasa's products which is produced with a make-to-stock system because the number of requests is relatively high. However, the pandemic conditions in 2020 resulted in a drastic decline in demand. Table 1 shows sales number of Paving block TP6 250.

Table 1. Sales number of Paving Block TP6 250

Month	Years		
	2019	2020	2021
Jan	2324	2853	1795
Feb	941	1686	195
Mar	1586	1729	1442
Apr	985	90	1075
Mei	1451	570	1015
Jun	794	1587	0
Jul	1043	285	664
Agu	1896	1213	1551
Sep	1173	1107	1238
Oct	780	0	1560
Nov	901	1086	1015
Des	2252	1347	1852
Total	16126	13553	13402

The pandemic condition has occurred in Indonesia since March 2020. From Table 1, it can be seen that there has been decreased number of requests for paving blocks from 2019 to 2021. Even though the company is aware of the declining demand, the

company cannot stop production activities because of the need to pay workers. Workers at CV Bayu Perkasa are paid according to the products produced, so if the company does not carry out the production process, the workers will not get wages. Table 2 shows CV Bayu Perkasa's Production and Sales Data in 2020.

Table 2. Production and Sales Data Comparison 2020

Month	Production of Paving Block TP6 250 (mtr/pcs)	Sales of Paving Block TP6 250 (mtr/pcs)	Inventory
1	3281	2853	428
2	3790	1686	2532
3	3465	1729	4268
4	1096	90	5274
5	519	570	5223
6	1267	1587	4903
7	1230	285	5848
8	0	1213	4635
9	1351	1107	4879
10	941	0	5820
11	0	1086	4734
12	0	1347	3387
Total	16940	13553	

Table 2 shows that in the 8th, 11th, and 12th months, the total production of paving blocks is 0. This is because there were other projects being worked on by CV Bayu Perkasa. CV Bayu Perkasa's problem is that the company does not yet have a strategic methodology to determine the number of products that need to be produced in the future, especially for products produced with a make-to-stock system. This resulted in product accumulation, especially during the pandemic, reaching 3387 meter/pcs.

Therefore, it is necessary to forecast the number of requests using the Artificial Neural Network (ANN) method. Modeling with mathematical methods such as ANN can optimize resources because their needs have been predicted previously **[2]**. ANN is a method that can use to make predictions with non-linear and complex data **[3]**. ANN has proven to be an efficient classification and predictive accuracy without prior system knowledge **[4]**. The ANN method can also be used for relatively small data conditions **[5]**. ANN predicts by exploring the relationship between variables to understand very complex structures, both linear and non-linear data, in a relatively short time **[6]**. The ANN method was used in this study because of the fluctuating number of requests for CV Bayu Perkasa and relatively few data. The artificial network method can learn from the data and is non-linear to identify the model's structure, and is effective in connecting input-output simulations with fluctuating and relatively little data **[7]**. According to Rosmala Sari and A. Sudiarso, ANN can predict aggregate product groups more accurately than traditional demand forecasting. Then aggregate planning is carried out from the forecasting results to produce stock arrangements much better than the initial conditions **[8]**.

The results of demand forecasting using ANN become data for optimizing production planning using the goal programming method. Goal programming (GP) is a method that can solve linear programming problems with more than one goal **[9]**. GP has been widely used as a multi-objective decision-making tool in past decades: in logistics, environmental studies, manufacturing, and economics **[10]**. GP can use several weighting criteria (Akbari, Jones, & Arabikhan, 2021). Several types of GP are distinguished in the weighting of the objective function, including Weighted Goal Programming (WGP), Lexicographic Goal Programming (LGP), and Minmax Goal Programming (Minmax GP) **[11]**. One of the uses of Linear Goal Programming has been to find solutions in the petroleum industry that have many goals **[12]**. GP can provide unwanted deviation variables and combine several objective functions **[13]**. Programming Objectives are used in the research at CV Bayu Perkasa because they have four functions: meeting demand, utilizing regular working hours, dealing with working hours, and production costs. Each objective function has different boundaries and priority scales.

2 Research Methodology

The research process begins with a literature study and field study to identify problems in the system. After finding the problem, then determine the objective research and determine the method of solving the problem. The method used in this study consists of 2 stages, namely: the demand forecasting process using the Artificial Neural Network (ANN) method and optimizing production planning using goal programming. Figure 1 explain the methodology of the research carried out.

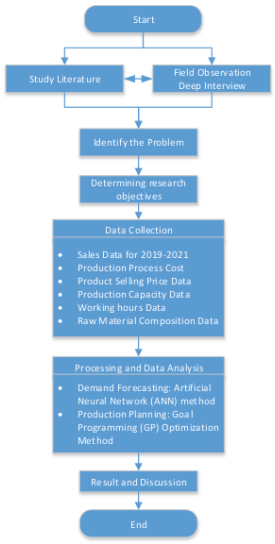

Figure 1. Research Methodology

3 Data Collection and Analysis

3.1 Demand Forecasting with Artificial Neural Network (ANN)

Forecasting is one of the methods commonly used to help organizations with capacity planning, goal setting, and anomaly detection **[14]**. Demand forecasting makes it easier for companies to determine the amount of production that needs to be done in the future and helps determine the amount of raw materials that need to be prepared in the production process **[15, 16]**. The method used in forecasting demand in this paper is artificial neural network (ANN). This is due to the fluctuating characteristics of the company's demand. The predicted product will only focus on Paving Block TP6 250 products as the product that has the highest demand and is a top priority for the company. Figure 2 shows the fluctuating number of requests for Paving Block TP6 250 in 2019 to 2021.

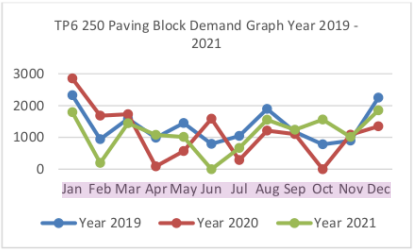

Figure 2. number of requests for Paving Block TP6 250 in 2019 to 2021

Plotting the demand listed in Figure 2, it is known that the data pattern is obtained randomly and does not form a certain trend, such as: seasonality, or others. Artificial neural networks that are deep learning can provide predictive output from stationary data and the linearity is not met **[17]**. Determination of the best network architecture is obtained from the training process and data testing. The data is divided into two, namely training and testing data. Preprocessing and data normalization is the first step before conducting the data training and testing process. Normalization functions to use the sigmoid activation function (binary), where the data must be transformed first because the output range of the sigmoid activation function is [0,1] **[18]**. Table 3 is the normalized TP6 250 Paving Block demand data.

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
1	0.751665	**13**	0.9	**25**	0.60333
2	0.363863	**14**	0.572766	**26**	0.154679
3	0.544725	**15**	0.584823	**27**	0.504346
4	0.3762	**16**	0.125237	**28**	0.401437
5	0.50687	**17**	0.259832	**29**	0.384613
6	0.322643	**18**	0.545005	**30**	0.1

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
7	0.392464	**19**	0.179916	**31**	0.28619
8	0.631651	**20**	0.440133	**32**	0.534911
9	0.428917	**21**	0.41041	**33**	0.447143
10	0.318717	**22**	0.1	**34**	0.537434
11	0.352646	**23**	0.404522	**35**	0.384613
12	0.731476	**24**	0.477708	**36**	0.619313

The artificial neural network architecture used in this study is a multi-layer network model with backpropagation and predetermined parameters, namely levenberg-marquardt (trainlm), with epoch 1000 with network model 12-32-10-1 and activation function [logsig, logsig , purelin]. The target MSE value is 0.00001. The data in table 3 is divided into 3 groups, training data, testing data, and output data. The input for training data is data number 1-12 (demand data for 2019), and the results will be compared with data number 13-24 (data demand for 2020). The training data input is data number 13-24, and the results will be compared with data number 25-36 (demand data for 2021). While the output data input is data numbers 25-36, and the result is a demand forecast for 2022.

The results of the training process with the 12-32-10-1 network are shown in Figure 3, which produces an MSE value of 2.9114^{e-}.The output of ANN at the training stage produces a good level of prediction accuracy. The training process aims to make the artificial neural network reach convergence and understand the network pattern from the parameters and algorithms that have been determined.

Figure 3. Network Training Results 12-32-10-1

The testing process requires a weight calculation, namely the calculation of the weight of the input to the layer, the calculation

of the weight of the layer to the output, the calculation of the bias weight to the layer, and the calculation of the bias weight to the output layer. The testing process by calculating weights and biases to get test results with an MSE of 0.017769 which is quite accurate.

The results of the ANN output in the testing process with initial weight and bias calculations, also produce demand forecasting for the period January 2022 to December 2022. The results of the demand forecasting that have been denormalized can be seen in table 4.

Table 4. Results of demand forecasting with the ANN method

Prediction Results Using ANN Method 12-32-10-1		
Period	Result Prediction	Denormalization Prediction
Jan-22	0.4769024	1392
Feb-22	0.272643162	686
Mar-22	0.424894043	1212
Apr-22	0.458526551	1328
May-22	0.344087869	933
Jun-22	0.464351997	1348
Jul-22	0.28976909	745
Aug-22	0.434675981	1246
Sep-22	0.214041042	484
Oct-22	0.408974241	1157
Nov-22	0.564908187	1696
Dec-22	0.292814266	756

Table 4 is the result of prediction demand forecasting from the ANN method. Table 4 is the result of prediction demand forecasting from the ANN method. These results become input for the production planning process. The limitation of demand data for other types of paving is overcome by using data on the proportion of requests for each paving from 2020-2021. The various types and quantities of requests and their proportions are shown in Table 5.

Table 5. Demand Proportion for each type of paving block

The number of Paving Request 2020-2021				
Paving Block TP6 250 (X1)	Paving Block TP6 350 (X2)	Paving Block TP8 250 (X3)	Paving Block TP8 350 (X4)	Paving Block Exagon (X5)
26955	2654	4491	110	872
Demand Proportion				
76.83%	7.57%	12.80%	0.31%	2.49%

3.2 Production Planning with Goal Programming (GP)

The goal programming model is used for complex problems that can solve more than 1 objective function with optimal solution results that the linear programming model cannot solve [19]. This study uses four objective functions in order of priority as follows, namely: fulfillment of demand, utilization of regular working hours, minimizing the number of overtime hours, and maximizing profits. So that the objective function is formed as follows:

$$Min\ Z = \sum_{i=1}^{5}(d_i^- + d_i^+) + d_6^+ + d_7^+ + d_8^+ + \sum_{i=9}^{12} d_i^+ \quad (3)$$

Determination of the decision variables is needed to determine the decision variables clearly for the unknown variables to proceed to the modeling stage [20]. The following decision variables are used in the CV Bahyu Perkasa goal programming optimization model below:

X1 = Product decision variable for paving block TP6 250
X2 = Product decision variable for paving TP6 350
X3 = Product decision variable for paving TP8 250
X4 = Product decision variable for paving TP8 350
X5 = Product decision variable for paving Exagon
$\boldsymbol{d_1^-}$ = Variable deviation under paving block request TP6 250
$\boldsymbol{d_1^+}$ = Variable deviation upper paving block request TP6 250
$\boldsymbol{d_2^-}$ = Variable deviation under paving block request TP6 350
$\boldsymbol{d_2^+}$ = Variable deviation upper paving block request TP6 350
$\boldsymbol{d_3^-}$ = Variable deviation under paving block request TP8 250
$\boldsymbol{d_3^+}$ = Variable deviation upper paving block request TP8 250
$\boldsymbol{d_4^-}$ = Variable deviation under paving block request TP8 350
$\boldsymbol{d_4^+}$ = Variable deviation upper paving block request TP8 350
$\boldsymbol{d_5^-}$ = Variable deviation under paving block request exagon
$\boldsymbol{d_5^+}$ = Variable deviation upper paving block request exagon
$\boldsymbol{d_6^-}$ = Variable deviation under regular working hours
$\boldsymbol{d_6^+}$ = Variable deviation upper regular working hours
$\boldsymbol{d_7^-}$ = Variable deviation under overtime hours
$\boldsymbol{d_7^+}$ = Variable deviation upper overtime hours
$\boldsymbol{d_8^-}$ = Variable deviation below production cost
$\boldsymbol{d_8^+}$ = Variable deviation above production cost
$\boldsymbol{d_9^-}$ = Variable deviation under the use of cement raw materials
$\boldsymbol{d_9^+}$ = Variable deviation upper the use of cement raw materials
$\boldsymbol{d_{10}^-}$ = Variable deviation under the use of sand raw materials
$\boldsymbol{d_{10}^+}$ = Variable deviation upper the use of sand raw materials
$\boldsymbol{d_{11}^-}$ = Variable deviation under the use of screening stone raw materials
$\boldsymbol{d_{11}^+}$ = Variable deviation upper the use of screening stone raw materials
$\boldsymbol{d_{12}^-}$ = Variable deviation under the use of rock ash raw material
$\boldsymbol{d_{12}^+}$ = Variable deviation upper the use of rock ash raw material

The fulfillment of each objective function has constraints built into a system's boundaries. The constraint function and each objective function are described as follows.

3.2.1 Request constraint function

The demand constraint function is created by adjusting the results of the demand forecast every month.

Constraint Function:

$$x_1 + d_1^- - d_1^+ = a_{1k} \quad (1)$$
$$x_2 + d_2^- - d_2^+ = a_{2k} \quad (2)$$
$$x_3 + d_3^- - d_3^+ = a_{3k} \quad (3)$$
$$x_4 + d_4^- - d_4^+ = a_{4k} \quad (4)$$
$$x_5 + d_5^- - d_5^+ = a_{5k} \quad (5)$$

Objective Function :

$$Min\ Z = \sum_{i=1}^{5}(d_i^- + d_i^+) \quad (6)$$

When :
d_i^- = Variable deviation under the paving block type request
d_i^+ = Variable deviation above the paving block type requesti
a_{ik} = Number of requests for the type of paving block
i = Types of paving block products (i = 1, 2, …5)

2 Regular working hours constraint function

The availability of working hours as a constraint function is used to see the relationship between production time and the

number of products produced. The formulation used to formulate this constraint function is as follows :

$$\sum_{i=1}^{5} A_i X_i \leq \sum_{j=1}^{12} JK_j \quad (7)$$

When :
A = Time required to produce 1 m/pcs paving block
X = Decision variables for the type of paving block product
JK = Number of available regular working hours
i = Types of paving block products (i = 1, 2, …5)
j = Month (1, 2,…. 12)

3.2.3 Overtime Constraint Function

The speed for producing all types of products, 1 m/pcs paving block, is the same, with 4 minutes of processing time required. If the demand is high, the company holds an overtime policy with maximum overtime of 20 working days in 1 month with a working time of 5 hours. Therefore, the maximum overtime allowed by the company every month is 100 hours, equivalent to 6000 minutes.

$$d_6^{+} + d_7^{-} - d_7^{+} = JL \quad (8)$$

$$d_6^{+} + d_7^{-} - d_7^{+} = 6000 \quad (9)$$

When :
d_7^{-} = Variable deviation under overtime hours
d_7^{+} = Variable deviation upper overtime hours
JL = Maximum capacity of overtime hours
The objective function is minimize overtime (d_7^{+}) :

$$Min\ Z = d_7^{+} \quad (10)$$

3.2.4 Production cost constraint function

Production costs are costs used in the production process. These costs consist of raw material, labor, and overhead costs. Overhead costs are costs the company must incur outside the operational costs of production. The total production cost for the tp6 250 paving block is Rp. 43,016.00 per m/pcs of paving blocks produced, as well as the production of other types of paving blocks. The company has a limit that the capital issued is Rp. 150,000,000.00 per month. So the constraint function is designed as follows:

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 \leq 150000000 \quad (11)$$

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 + d_8^{-} - d_8^{+} = 150000000 \quad (12)$$

Objective Function :

$$Min\ Z = d_8^{+} \quad (13)$$

3.2.5 Raw material constraint function

The amount of raw material used for each product must be less than or equal to the availability of these raw materials. The formulation of the formula used is as follows:

$$\sum_{l=1}^{4} \sum_{i=1}^{5} B_l X_i \leq BT_{il} \quad (14)$$

When :
B = The amount of raw material used for each type of paving
x = The decision variable for the paving block type
BT = Amount of raw material availability
i = The type of Paving Block
l = The type of material (l = 1, 2, … 4)
B_1 = Amount of cement raw material usage
B_2 = Amount of sand raw material usage
B_3 = Amount of screening stone raw material usage
B_4 = Amount of use of stone ash raw materials

So, the formula for the constraint function of the use of raw materials to produce 1 m/pcs paving block every month is:

Cement (Kg)

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 \leq 128000 \quad (15)$$

Sand (m^3)

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 \leq 840 \quad (16)$$

Screening stone (m^3)

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 \leq 840 \quad (17)$$

Stone ash (m^3)

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 \leq 644 \quad (18)$$

Constrain :

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 + d_9^{-} - d_9^{+} = 128000 \quad (19)$$

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 + d_{10}^{-} - d_{10}^{+} = 840 \quad (20)$$

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 + d_{11}^{-} - d_{11}^{+} = 840 \quad (21)$$

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 + d_{12}^{-} - d_{12}^{+} = 644 \quad (22)$$

Objective Function :

$$Min\ Z = \sum_{i=9}^{12} d_i^{+} \quad (23)$$

1.2.6 Goal Programming Modeling Results

Production planning using LINGO is carried out in a monthly period. As a result, all objective functions are achieved. In addition, production costs in January also decreased by Rp. 50,780,680 from the monthly capital of Rp. 150,000,000.00 determined by the company. So the calculation of the production planning resulted in a total cost reduction of Rp. 992,057,740.00 from Rp. 1,800,000,000.00 or equivalent to a 55.11% decrease in production costs.

In the model results obtained, there is still a large surplus of raw materials, and regular working and overtime hours have not been used. The company can modify the model if it wants to maximize its working hours to be more productive by adding existing restrictions.

4 Conclusion and Recommendation

The results that can be concluded from this study are as follow:

1. Forecasting results using the Artificial Neural Network method provide an MSE error value accuracy rate of 0.017769 for Paving Block TP6 250 products in the upcoming 2022 period. The results of monthly demand forecasting in 2022 are in Table 4. The result of the ANN forecasting method can be continued for the following years.

2. The results of optimization of production planning using goal programming with LINGO show that all objective functions can be fulfilled. The four objective functions are the fulfillment of demand with the right quantity, the goal of normal working time, minimizing overtime hours, and minimizing production costs. Based on the calculation of the optimization of production planning using goal programming, there is a decrease in production costs in 1 year of Rp. 992,057,740.00 from the company's capital of Rp. 150,000,000.00 per month or equivalent to 55.11%. The formulation of the mathematical model that has been made can solve the same problem in the following periods. Production planning using the optimization method with goal programming is more useful and produces optimal solutions than production planning for the company's current condition.

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REFERENCE

[1] I. N. Pujawan and M. E. R, Supply Chain Management, Surabaya: Guna Widya, 2010.

[2] B. Işcan, "ANN modeling for justification of thermodynamic analysis of experimental applications on combustion parameters of a diesel engine using diesel and safflower biodiesel fuels," *Fuel*, p. 117291, 2020.

[3] W. R. B. T. D. I. N. E. N. N. K. A. A. M. He, "Using of Artificial Neural Networks (ANNs) to predict the thermal conductivity of Zinc Oxide–Silver (50%–50%)/Water hybrid Newtonian nanofluid," *International Communications in Heat and Mass Transfer*, p. 104645, 2020.

[4] L. L. Jiang and D. L. Maskell, "Automatic Fault Detection and Diagnosis for Photovoltaic Systems using Combined Artificial Neural Network and Analytical Based Methods," in *International Joint Conference on Neural Networks (IJCNN)*, Canada, 2015.

[5] J. Sun, Z. Zhao and Y. Zhang, "Determination of three dimensional hydraulic conductivities using a combined analytical/neural network model," *Tunnelling and Underground Space Technology*, vol. 26, no. 2, p. 310–319, 2011.

[6] P. . H. Thike, Z. Zhao, P. Shi and Y. Jin, "ignificance of artificial neural network analytical models in materials' performance prediction," *Bulletin of Materials Science*, vol. 43, no. 1, pp. 1-22, 2020.

[7] B. I. Setiawan and R. , "Neural Networks Application For River Flow Prediction," in *Proceedings of the Simulation and Computing Technology Workshop and Applications*, Jakarta, 2004.

[8] I. R. Sari and A. Sudiarso, "Aggregate Production Planning Based on Demand Forecasting Using Artificial Neural Networks in IKM X," in *Proc. SENTI-UGM*, Yogyakarta, 2015.

[9] W. Anggraeni, R. A. Vinarti, R. Tyasnurita and J. Permatasari, "Production planning optimization using goal programming method in Habibah Busana," *Journal of Advanced Management Science*, vol. 3, no. 4, pp. 270-275, 2015.

[10] D. Broza, N. Vanzettib, G. Corsano and J. M. Montagnab, "Goal programming application for the decision support in the daily production planning of sawmills," *Forest Policy and Economics*, pp. 29-40, 2019.

[11] C. M. Defalque, A. F. d. Silva and F. A. S. Marins, "Goal programming model applied to waste paper logistics processes," *Applied Mathematical Modelling*, vol. 98, pp. 185-206, 2021.

[12] C. A. Kumar and T. Srinivas, "Using goal programming for transportation planning decisions problem Using goal programming for transportation planning decisions problem," *Materials Today: Proceedings*, 2020.

[13] W. A. Oliveira, D. J. Fiorotto, X. Song and D. F. Jones, "An extended goal programming model for the multiobjective integrated lot-sizing and cutting stock problem," *European Journal of Operational Research*, vol. 295, no. 3, pp. 996-1007, 2021.

[14] S. J. Taylor and B. Letham, "Forecasting at Scale," *The American Statistician*, vol. 72, no. 1, pp. 37-45, 2017.

[15] J.-H. Bose, V. Flunkert, J. Gasthaus, T. Januschowski, D. Lange, D. Salinas, S. Schelter, M. Seeger and Y. Wang, "Probabilistic Demand Forecasting at Scale," *Proceedings of the VLDB Endowment*, vol. 10, no. 12, pp. 1694-1705, 2017.

[16] I. Ghalehkhondabi, E. Ardjmand, G. R. Weckman and W. A. Young, "An overview of energy demand forecasting methods," *Energy Systems*, vol. 8, no. 2, pp. 411-447, 2015.

[17] S. Mardliyah, M. Y. Fajar and F. H. Badruzzaman, "Use of Forecasting and Goal Programming in Optimizing Rice Production Planning," in *Bandung Conference Series: Mathematics*, Bandung, 2022.

[18] R. K. Renaldi, I. A. Marie, P. Moengin, N. J. W and N. , "Demand Forecasting Using Artificial Neural Networks and Production Planning Using Linear Programming in Aluminum Companies," *Jurnal Teknik Industri*, pp. 196-203, 2021.

[19] N. Sen and M. Nandi, "Goal programming, its application in management sectors–special attention into plantation management: a review," *nternational journal of scientific and research publications* , vol. 2, no. 9, pp. 1-6, 2012.

[20] S. Hotniar, Riset Operasional Seri Pemograman Linier, Yogyakarta: Graha Ilmu, 2005.

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Optimization of Production Planning Using Goal Programming and Inventory Control Based on Demand Forecasting Using Neural Networks on CV Bahyu Perkasa

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Optimization of Production Planning Using Goal Programming and Inventory Control Based On Demand Forecasting Using Neural Networks On CV Bahyu Perkasa

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ABSTRACT

CV Bahyu Perkasa is a company engaged in the concrete construction industry. One of the products produced is paving block. The number of fluctuating demands makes the company decide to stockpile products and procure raw materials regularly to meet consumer demand. This was Born in over-production and overstock. Therefore, a consumer demand forecasting method is needed so that it can minimize production costs and maximize profits. In addition, inventory control methods are needed to reduce storage costs and ordering costs for raw materials. The method used for demand forecasting is an artificial neural network with an MSE error accuracy rate of 0.017769. Forecasting results are used to optimize production planning using goal programming and inventory control planning using MRP. The results of the goal programming optimization model with priority determination produce an optimal solution in fulfilling consumer demand and minimizing production costs of Rp. 99,205,774.00.

CCS CONCEPTS

• Applied Computing ~ Operations Research ~ Industry and Manufacturing • Applied Computing ~ Operations Research ~ Forecasting

KEYWORDS

Optimization, Production Planning, Forecasting, Artificial Neural Network, Goal Programming

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1 Introduction

CV Bayu Perkasa is a company engaged in concrete construction. The production process applied by the company uses two methods: make to stock and make to order. Products made with make-to-stock are products with a high enough demand, while products made with make-to-order are products with unique specifications from consumers, and the number of requests is low [1].

The paving block is one of CV Bayu Perkasa's products which is produced with a make-to-stock system because the number of requests is relatively high. However, the pandemic conditions in 2020 resulted in a drastic decline in demand. Table 1 shows sales number of Paving block TP6 250.

Table 1. Sales number of Paving Block TP6 250

Month	Years		
	2019	2020	2021
Jan	2324	2853	1795
Feb	941	1686	195
Mar	1586	1729	1442
Apr	985	90	1075
Mei	1451	570	1015
Jun	794	1587	0
Jul	1043	285	664
Agu	1896	1213	1551
Sep	1173	1107	1238
Oct	780	0	1560
Nov	901	1086	1015
Des	2252	1347	1852
Total	16126	13553	13402

The pandemic condition has occurred in Indonesia since March 2020. From Table 1, it can be seen that there has been decreased number of requests for paving blocks from 2019 to 2021. Even though the company is aware of the declining demand, the

company cannot stop production activities because of the need to pay workers. Workers at CV Bayu Perkasa are paid according to the products produced, so if the company does not carry out the production process, the workers will not get wages. Table 2 shows CV Bayu Perkasa's Production and Sales Data in 2020.

Table 2. Production and Sales Data Comparison 2020

Month	Production of Paving Block TP6 250 (mtr/pcs)	Sales of Paving Block TP6 250 (mtr/pcs)	Inventory
1	3281	2853	428
2	3790	1686	2532
3	3465	1729	4268
4	1096	90	5274
5	519	570	5223
6	1267	1587	4903
7	1230	285	5848
8	0	1213	4635
9	1351	1107	4879
10	941	0	5820
11	0	1086	4734
12	0	1347	3387
Total	16940	13553	

Table 2 shows that in the 8th, 11th, and 12th months, the total production of paving blocks is 0. This is because there were other projects being worked on by CV Bayu Perkasa. CV Bayu Perkasa's problem is that the company does not yet have a strategic methodology to determine the number of products that need to be produced in the future, especially for products produced with a make-to-stock system. This resulted in product accumulation, especially during the pandemic, reaching 3387 meter/pcs.

Therefore, it is necessary to forecast the number of requests using the Artificial Neural Network (ANN) method. Modeling with mathematical methods such as ANN can optimize resources because their needs have been predicted previously **[2]**. ANN is a method that can use to make predictions with non-linear and complex data **[3]**. ANN has proven to be an efficient classification and predictive accuracy without prior system knowledge **[4]**. The ANN method can also be used for relatively small data conditions **[5]**. ANN predicts by exploring the relationship between variables to understand very complex structures, both linear and non-linear data, in a relatively short time **[6]**. The ANN method was used in this study because of the fluctuating number of requests for CV Bayu Perkasa and relatively few data. The artificial network method can learn from the data and is non-linear to identify the model's structure, and is effective in connecting input-output simulations with fluctuating and relatively little data **[7]**. According to Rosmala Sari and A. Sudiarso, ANN can predict aggregate product groups more accurately than traditional demand forecasting. Then aggregate planning is carried out from the forecasting results to produce stock arrangements much better than the initial conditions **[8]**.

The results of demand forecasting using ANN become data for optimizing production planning using the goal programming method. Goal programming (GP) is a method that can solve linear programming problems with more than one goal **[9]**. GP has been widely used as a multi-objective decision-making tool in past decades: in logistics, environmental studies, manufacturing, and economics **[10]**. GP can use several weighting criteria (Akbari, Jones, & Arabikhan, 2021). Several types of GP are distinguished in the weighting of the objective function, including Weighted Goal Programming (WGP), Lexicographic Goal Programming (LGP), and Minmax Goal Programming (Minmax GP) **[11]**. One of the uses of Linear Goal Programming has been to find solutions in the petroleum industry that have many goals **[12]**. GP can provide unwanted deviation variables and combine several objective functions **[13]**. Programming Objectives are used in the research at CV Bayu Perkasa because they have four functions: meeting demand, utilizing regular working hours, dealing with working hours, and production costs. Each objective function has different boundaries and priority scales.

2 Research Methodology

The research process begins with a literature study and field study to identify problems in the system. After finding the problem, then determine the objective research and determine the method of solving the problem. The method used in this study consists of 2 stages, namely: the demand forecasting process using the Artificial Neural Network (ANN) method and optimizing production planning using goal programming. Figure 1 explain the methodology of the research carried out.

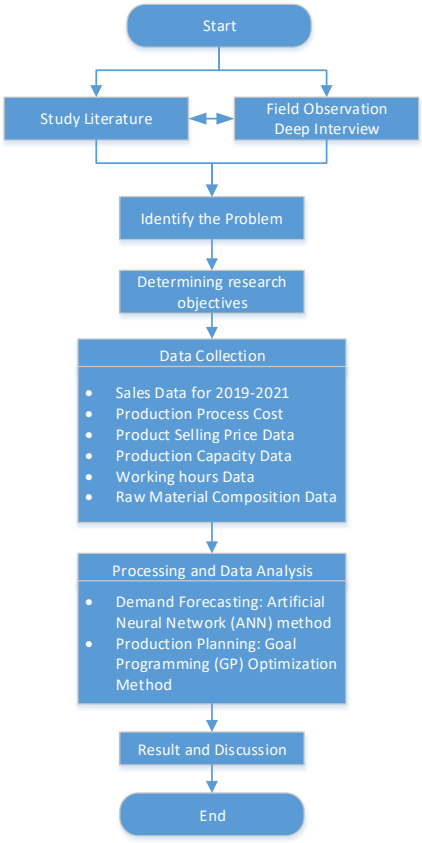

Figure 1. Research Methodology

3 Data Collection and Analysis

3.1 Demand Forecasting with Artificial Neural Network (ANN)
Forecasting is one of the methods commonly used to help organizations with capacity planning, goal setting, and anomaly detection **[14]**. Demand forecasting makes it easier for companies to determine the amount of production that needs to be done in the future and helps determine the amount of raw materials that need to be prepared in the production process **[15, 16]**. The method used in forecasting demand in this paper is artificial neural network (ANN). This is due to the fluctuating characteristics of the company's demand. The predicted product will only focus on Paving Block TP6 250 products as the product that has the highest demand and is a top priority for the company. Figure 2 shows the fluctuating number of requests for Paving Block TP6 250 in 2019 to 2021.

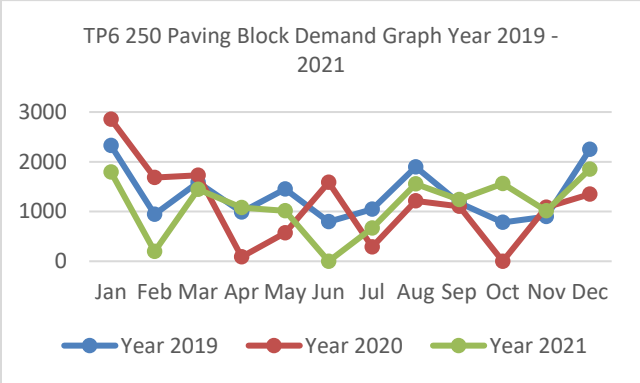

Figure 2. number of requests for Paving Block TP6 250 in 2019 to 2021

Plotting the demand listed in Figure 2, it is known that the data pattern is obtained randomly and does not form a certain trend, such as: seasonality, or others. Artificial neural networks that are deep learning can provide predictive output from stationary data and the linearity is not met **[17]**. Determination of the best network architecture is obtained from the training process and data testing. The data is divided into two, namely training and testing data. Preprocessing and data normalization is the first step before conducting the data training and testing process. Normalization functions to use the sigmoid activation function (binary), where the data must be transformed first because the output range of the sigmoid activation function is [0,1] **[18]**. Table 3 is the normalized TP6 250 Paving Block demand data.

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
1	0.751665	**13**	0.9	**25**	0.60333
2	0.363863	**14**	0.572766	**26**	0.154679
3	0.544725	**15**	0.584823	**27**	0.504346
4	0.3762	**16**	0.125237	**28**	0.401437
5	0.50687	**17**	0.259832	**29**	0.384613
6	0.322643	**18**	0.545005	**30**	0.1

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
7	0.392464	**19**	0.179916	**31**	0.28619
8	0.631651	**20**	0.440133	**32**	0.534911
9	0.428917	**21**	0.41041	**33**	0.447143
10	0.318717	**22**	0.1	**34**	0.537434
11	0.352646	**23**	0.404522	**35**	0.384613
12	0.731476	**24**	0.477708	**36**	0.619313

The artificial neural network architecture used in this study is a multi-layer network model with backpropagation and predetermined parameters, namely levenberg-marquardt (trainlm), with epoch 1000 with network model 12-32-10-1 and activation function [logsig, logsig , purelin]. The target MSE value is 0.00001. The data in table 3 is divided into 3 groups, training data, testing data, and output data. The input for training data is data number 1-12 (demand data for 2019), and the results will be compared with data number 13-24 (data demand for 2020). The training data input is data number 13-24, and the results will be compared with data number 25-36 (demand data for 2021). While the output data input is data numbers 25-36, and the result is a demand forecast for 2022.

The results of the training process with the 12-32-10-1 network are shown in Figure 3, which produces an MSE value of 2.9114^{e-}.The output of ANN at the training stage produces a good level of prediction accuracy. The training process aims to make the artificial neural network reach convergence and understand the network pattern from the parameters and algorithms that have been determined.

Figure 3. Network Training Results 12-32-10-1

The testing process requires a weight calculation, namely the calculation of the weight of the input to the layer, the calculation

of the weight of the layer to the output, the calculation of the bias weight to the layer, and the calculation of the bias weight to the output layer. The testing process by calculating weights and biases to get test results with an MSE of 0.017769 which is quite accurate.

The results of the ANN output in the testing process with initial weight and bias calculations, also produce demand forecasting for the period January 2022 to December 2022. The results of the demand forecasting that have been denormalized can be seen in table 4.

Table 4. Results of demand forecasting with the ANN method

Prediction Results Using ANN Method 12-32-10-1		
Period	Result Prediction	Denormalization Prediction
Jan-22	0.4769024	1392
Feb-22	0.272643162	686
Mar-22	0.424894043	1212
Apr-22	0.458526551	1328
May-22	0.344087869	933
Jun-22	0.464351997	1348
Jul-22	0.28976909	745
Aug-22	0.434675981	1246
Sep-22	0.214041042	484
Oct-22	0.408974241	1157
Nov-22	0.564908187	1696
Dec-22	0.292814266	756

Table 4 is the result of prediction demand forecasting from the ANN method. Table 4 is the result of prediction demand forecasting from the ANN method. These results become input for the production planning process. The limitation of demand data for other types of paving is overcome by using data on the proportion of requests for each paving from 2020-2021. The various types and quantities of requests and their proportions are shown in Table 5.

Table 5. Demand Proportion for each type of paving block

The number of Paving Request 2020-2021				
Paving Block TP6 250 (X1)	Paving Block TP6 350 (X2)	Paving Block TP8 250 (X3)	Paving Block TP8 350 (X4)	Paving Block Exagon (X5)
26955	2654	4491	110	872
Demand Proportion				
76.83%	7.57%	12.80%	0.31%	2.49%

3.2 Production Planning with Goal Programming (GP)

The goal programming model is used for complex problems that can solve more than 1 objective function with optimal solution results that the linear programming model cannot solve [19]. This study uses four objective functions in order of priority as follows, namely: fulfillment of demand, utilization of regular working hours, minimizing the number of overtime hours, and maximizing profits. So that the objective function is formed as follows:

$$Min\ Z = \sum_{i=1}^{5}\left(d_i^{-} + d_i^{+}\right) + d_6^{+} + d_7^{+} + d_8^{+} + \sum_{i=9}^{12} d_i^{+} \quad (3)$$

Determination of the decision variables is needed to determine the decision variables clearly for the unknown variables to proceed to the modeling stage [20]. The following decision variables are used in the CV Bahyu Perkasa goal programming optimization model below:

X1 = Product decision variable for paving block TP6 250
X2 = Product decision variable for paving TP6 350
X3 = Product decision variable for paving TP8 250
X4 = Product decision variable for paving TP8 350
X5 = Product decision variable for paving Exagon
$\boldsymbol{d_1}^{-}$= Variable deviation under paving block request TP6 250
$\boldsymbol{d_1}^{+}$= Variable deviation upper paving block request TP6 250
$\boldsymbol{d_2}^{-}$= Variable deviation under paving block request TP6 350
$\boldsymbol{d_2}^{+}$= Variable deviation upper paving block request TP6 350
$\boldsymbol{d_3}^{-}$= Variable deviation under paving block request TP8 250
$\boldsymbol{d_3}^{+}$= Variable deviation upper paving block request TP8 250
$\boldsymbol{d_4}^{-}$= Variable deviation under paving block request TP8 350
$\boldsymbol{d_4}^{+}$= Variable deviation upper paving block request TP8 350
$\boldsymbol{d_5}^{-}$= Variable deviation under paving block request exagon
$\boldsymbol{d_5}^{+}$= Variable deviation upper paving block request exagon
$\boldsymbol{d_6}^{-}$= Variable deviation under regular working hours
$\boldsymbol{d_6}^{+}$= Variable deviation upper regular working hours
$\boldsymbol{d_7}^{-}$= Variable deviation under overtime hours
$\boldsymbol{d_7}^{+}$= Variable deviation upper overtime hours
$\boldsymbol{d_8}^{-}$= Variable deviation below production cost
$\boldsymbol{d_8}^{+}$= Variable deviation above production cost
$\boldsymbol{d_9}^{-}$= Variable deviation under the use of cement raw materials
$\boldsymbol{d_9}^{+}$= Variable deviation upper the use of cement raw materials
$\boldsymbol{d_{10}}^{-}$= Variable deviation under the use of sand raw materials
$\boldsymbol{d_{10}}^{+}$= Variable deviation upper the use of sand raw materials
$\boldsymbol{d_{11}}^{-}$= Variable deviation under the use of screening stone raw materials
$\boldsymbol{d_{11}}^{+}$= Variable deviation upper the use of screening stone raw materials
$\boldsymbol{d_{12}}^{-}$= Variable deviation under the use of rock ash raw material
$\boldsymbol{d_{12}}^{+}$= Variable deviation upper the use of rock ash raw material

The fulfillment of each objective function has constraints built into a system's boundaries. The constraint function and each objective function are described as follows.

3.2.1 Request constraint function

The demand constraint function is created by adjusting the results of the demand forecast every month.

Constraint Function:

$$x_1 + d_1^{-} - d_1^{+} = a_{1k} \quad (1)$$
$$x_2 + d_2^{-} - d_2^{+} = a_{2k} \quad (2)$$
$$x_3 + d_3^{-} - d_3^{+} = a_{3k} \quad (3)$$
$$x_4 + d_4^{-} - d_4^{+} = a_{4k} \quad (4)$$
$$x_5 + d_5^{-} - d_5^{+} = a_{5k} \quad (5)$$

Objective Function :

$$Min\ Z = \sum_{i=1}^{5}\left(d_i^{-} + d_i^{+}\right) \quad (6)$$

When :

d_i^{-}= Variable deviation under the paving block type request
d_i^{+}= Variable deviation above the paving block type requesti
a_{ik}= Number of requests for the type of paving block
i= Types of paving block products (i = 1, 2, …5)

3.2.2 Regular working hours constraint function

The availability of working hours as a constraint function is used to see the relationship between production time and the

number of products produced. The formulation used to formulate this constraint function is as follows :

$$\sum_{i=1}^{5} A_i X_i \leq \sum_{j=1}^{12} JK_j \quad (7)$$

When :
A = Time required to produce 1 m/pcs paving block
X = Decision variables for the type of paving block product
JK = Number of available regular working hours
i = Types of paving block products (i = 1, 2, …5)
j = Month (1, 2,…. 12)

3.2.3 Overtime Constraint Function

The speed for producing all types of products, 1 m/pcs paving block, is the same, with 4 minutes of processing time required. If the demand is high, the company holds an overtime policy with maximum overtime of 20 working days in 1 month with a working time of 5 hours. Therefore, the maximum overtime allowed by the company every month is 100 hours, equivalent to 6000 minutes.

$$d_6{}^{+} + d_7{}^{-} - d_7{}^{+} = JL \quad (8)$$

$$d_6{}^{+} + d_7{}^{-} - d_7{}^{+} = 6000 \quad (9)$$

When :
$d_7{}^{-}$ = Variable deviation under overtime hours
$d_7{}^{+}$ = Variable deviation upper overtime hours
JL = Maximum capacity of overtime hours
The objective function is minimize overtime ($d_7{}^{+}$) :

$$Min\ Z = d_7{}^{+} \quad (10)$$

3.2.4 Production cost constraint function

Production costs are costs used in the production process. These costs consist of raw material, labor, and overhead costs. Overhead costs are costs the company must incur outside the operational costs of production. The total production cost for the tp6 250 paving block is Rp. 43,016.00 per m/pcs of paving blocks produced, as well as the production of other types of paving blocks. The company has a limit that the capital issued is Rp. 150,000,000.00 per month. So the constraint function is designed as follows:

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 \leq 150000000 \quad (11)$$

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 + d_8{}^{-} - d_8{}^{+} = 150000000 \quad (12)$$

Objective Function :

$$Min\ Z = d_8{}^{+} \quad (13)$$

3.2.5 Raw material constraint function

The amount of raw material used for each product must be less than or equal to the availability of these raw materials. The formulation of the formula used is as follows:

$$\sum_{l=1}^{4}\sum_{i=1}^{5} B_l X_i \leq BT_{il} \quad (14)$$

When :
B = The amount of raw material used for each type of paving
x = The decision variable for the paving block type
BT = Amount of raw material availability
i = The type of Paving Block
l = The type of material (l = 1, 2, … 4)
B_1 = Amount of cement raw material usage
B_2 = Amount of sand raw material usage
B_3 = Amount of screening stone raw material usage
B_4 = Amount of use of stone ash raw materials

So, the formula for the constraint function of the use of raw materials to produce 1 m/pcs paving block every month is:

Cement (Kg)

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 \leq 128000 \quad (15)$$

Sand (m^3)

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 \leq 840 \quad (16)$$

Screening stone (m^3)

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 \leq 840 \quad (17)$$

Stone ash (m^3)

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 \leq 644 \quad (18)$$

Constrain :

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 + d_9{}^{-} - d_9{}^{+} = 128000 \quad (19)$$

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 + d_{10}{}^{-} - d_{10}{}^{+} = 840 \quad (20)$$

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 + d_{11}{}^{-} - d_{11}{}^{+} = 840 \quad (21)$$

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 + d_{12}{}^{-} - d_{12}{}^{+} = 644 \quad (22)$$

Objective Function :

$$Min\ Z = \sum_{i=9}^{12} d_i{}^{+} \quad (23)$$

1.2.6 Goal Programming Modeling Results

Production planning using LINGO is carried out in a monthly period. As a result, all objective functions are achieved. In addition, production costs in January also decreased by Rp. 50,780.680 from the monthly capital of Rp. 150,000,000.00 determined by the company. So the calculation of the production planning resulted in a total cost reduction of Rp. 992,057,740.00 from Rp. 1,800,000,000.00 or equivalent to a 55.11% decrease in production costs.

In the model results obtained, there is still a large surplus of raw materials, and regular working and overtime hours have not been used. The company can modify the model if it wants to maximize its working hours to be more productive by adding existing restrictions.

4 Conclusion and Recommendation

The results that can be concluded from this study are as follow**:**

1. Forecasting results using the Artificial Neural Network method provide an MSE error value accuracy rate of 0.017769 for Paving Block TP6 250 products in the upcoming 2022 period. The results of monthly demand forecasting in 2022 are in Table 4. The result of the ANN forecasting method can be continued for the following years.

2. The results of optimization of production planning using goal programming with LINGO show that all objective functions can be fulfilled. The four objective functions are the fulfillment of demand with the right quantity, the goal of normal working time, minimizing overtime hours, and minimizing production costs. Based on the calculation of the optimization of production planning using goal programming, there is a decrease in production costs in 1 year of Rp. 992,057,740.00 from the company's capital of Rp. 150,000,000.00 per month or equivalent to 55.11%. The formulation of the mathematical model that has been made can solve the same problem in the following periods. Production planning using the optimization method with goal programming is more useful and produces optimal solutions than production planning for the company's current condition.

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REFERENCE

[1] I. N. Pujawan and M. E. R, Supply Chain Management, Surabaya: Guna Widya, 2010.

[2] B. Işcan, "ANN modeling for justification of thermodynamic analysis of experimental applications on combustion parameters of a diesel engine using diesel and safflower biodiesel fuels," *Fuel*, p. 118391, 2020.

[3] W. R. B. T. D. I. N. E. N. N. K. A. A. M. He, "Using of Artificial Neural Networks (ANNs) to predict the thermal conductivity of Zinc Oxide–Silver (50%–50%)/Water hybrid Newtonian nanofluid," *International Communications in Heat and Mass Transfer*, p. 104645, 2020.

[4] L. L. Jiang and D. L. Maskell, "Automatic Fault Detection and Diagnosis for Photovoltaic Systems using Combined Artificial Neural Network and Analytical Based Methods," in *International Joint Conference on Neural Networks (IJCNN)*, Canada, 2015.

[5] J. Sun, Z. Zhao and Y. Zhang, "Determination of three dimensional hydraulic conductivities using a combined analytical/neural network model," *Tunnelling and Underground Space Technology*, vol. 26, no. 2, p. 310–319, 2011.

[6] P. . H. Thike, Z. Zhao, P. Shi and Y. Jin, "ignificance of artificial neural network analytical models in materials' performance prediction," *Bulletin of Materials Science*, vol. 43, no. 1, pp. 1-22, 2020.

[7] B. I. Setiawan and R. , "Neural Networks Application For River Flow Prediction," in *Proceedings of the Simulation and Computing Technology Workshop and Applications*, Jakarta, 2004.

[8] I. R. Sari and A. Sudiarso, "Aggregate Production Planning Based on Demand Forecasting Using Artificial Neural Networks in IKM X," in *Proc. SENTI-UGM*, Yogyakarta, 2015.

[9] W. Anggraeni, R. A. Vinarti, R. Tyasnurita and J. Permatasari, "Production planning optimization using goal programming method in Habibah Busana," *Journal of Advanced Management Science*, vol. 3, no. 4, pp. 270-275, 2015.

[10] D. Broza, N. Vanzettib, G. Corsano and J. M. Montagnab, "Goal programming application for the decision support in the daily production planning of sawmills," *Forest Policy and Economics*, pp. 29-40, 2019.

[11] C. M. Defalque, A. F. d. Silva and F. A. S. Marins, "Goal programming model applied to waste paper logistics processes," *Applied Mathematical Modelling*, vol. 98, pp. 185-206, 2021.

[12] C. A. Kumar and T. Srinivas, "Using goal programming for transportation planning decisions problem Using goal programming for transportation planning decisions problem," *Materials Today: Proceedings*, 2020.

[13] W. A. Oliveira, D. J. Fiorotto, X. Song and D. F. Jones, "An extended goal programming model for the multiobjective integrated lot-sizing and cutting stock problem," *European Journal of Operational Research*, vol. 295, no. 3, pp. 996-1007, 2021.

[14] S. J. Taylor and B. Letham, "Forecasting at Scale," *The American Statistician*, vol. 72, no. 1, pp. 37-45, 2017.

[15] J.-H. Bose, V. Flunkert, J. Gasthaus, T. Januschowski, D. Lange, D. Salinas, S. Schelter, M. Seeger and Y. Wang, "Probabilistic Demand Forecasting at Scale," *Proceedings of the VLDB Endowment*, vol. 10, no. 12, pp. 1694-1705, 2017.

[16] I. Ghalehkhondabi, E. Ardjmand, G. R. Weckman and W. A. Young, "An overview of energy demand forecasting methods," *Energy Systems*, vol. 8, no. 2, pp. 411-447, 2015.

[17] S. Mardliyah, M. Y. Fajar and F. H. Badruzzaman, "Use of Forecasting and Goal Programming in Optimizing Rice Production Planning," in *Bandung Conference Series: Mathematics*, Bandung, 2022.

[18] R. K. Renaldi, I. A. Marie, P. Moengin, N. J. W and N. , "Demand Forecasting Using Artificial Neural Networks and Production Planning Using Linear Programming in Aluminum Companies," *Jurnal Teknik Industri*, pp. 196-203, 2021.

[19] N. Sen and M. Nandi, "Goal programming, its application in management sectors–special attention into plantation management: a review," *nternational journal of scientific and research publications* , vol. 2, no. 9, pp. 1-6, 2012.

[20] S. Hotniar, Riset Operasional Seri Pemograman Linier, Yogyakarta: Graha Ilmu, 2005.