APPLICATION OF THE GOAL PROGRAMMING IN WOOD PROCESSING PRODUCTION PLANNING

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Ajla Piljević

Examiner(s): Prof. Dr. Mugdim Pašić

Assoc. Prof. Niko Kinnunen

Prof. Michael Höck

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Supervisor / scientific member (HU):	Prof. Dr. Mugdim Pašić
Supervisor / scientific member (LUT):	Assoc. Prof. Niko Kinnunen
Supervisor / scientific member (TUBAF):	Prof. Michael Höck

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(Prof. Dr. Mugdim Pašić)	(Assoc. Prof. Niko Kinnunen)	(Prof. Michael Höck)
Supervisor / member HU	Supervisor / member LUT	Supervisor / member TUBAF

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ABSTRACT

Lappeenranta–Lahti University of Technology LUT

LUT School of Engineering Science

International Master of Science in Engineering, Entrepreneurship, and Resources (MSc. ENTER)

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Application of the goal programming in wood processing production planning

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Wood-processing companies often try to achieve multiple conflicting goals simultaneously during production planning. In this thesis, two mixed-integer lexicographic goal programming models were developed to demonstrate the applicability and benefits of using goal programming as an optimisation tool to help with production planning. The models were formulated using data provided by the chair manufacturer Wood Team d.o.o. for three selected chair models and three production departments: machining, upholstery and assembly. Both models included the same goals but assigned them different priority orders. These goals were to reach a target profit, keep CO_2 emission costs within an acceptable level, reduce underproduction relative to average daily demand, and minimise underutilised labour capacity and overtime. Microsoft Excel Solver was used to solve the models with a sequential lexicographic procedure. The results showed that different priority orders led to different production plans and outcomes regarding labour utilisation, overtime and demand fulfilment, highlighting the importance of carefully assigning priorities. The findings indicate that goal programming, with its ability to consider multiple conflicting goals, can

support production planning. Goal programming has many variants, and the models are flexible, allowing them to be further adapted and developed when necessary. Consequently, goal programming can serve as a useful decision-support tool for testing the potential effects of managerial decisions before their implementation.

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SYMBOLS AND ABBREVIATIONS

Roman characters

A	matrix of all the coefficients in the linear programming constraints	
B	daily CO_2 emission cost benchmark	[EUR/day]
b	right-hand-side vector in the general LP formulation	
c	vector of objective-function coefficients in the general LP formulation	
c_D	estimated daily wage cost per worker	[EUR/worker]
c_H	average hourly labour cost	[EUR/h]
c_{OTP}	additional overtime premium	[EUR/h, EUR/min]
c_{ij}	coefficient of decision variable x_j in the i-th goal constraint in the general GP formulation	
D_j	average daily demand	[units/day]
d_i^-	negative deviation variable	
d_i^+	positive deviation variable	
e_i	CO_2 footprint of chair model i	[kg CO_2e/unit]
K	number of priority levels in the general GP formulation	
k_i	costs of CO_2 emissions per unit of chair model i	[EUR/unit]
l	number of the decision variables in the general GP formulation	

m	number of the goal constraints in the general GP formulation	
M1, M2, M3	selected chair models	
n	number of decision variables in the general LP formulation	
P	total daily profit	[EUR/day]
P_k	the *k*-th priority level in the pre-emptive hierarchy in the general GP formulation	
P_j	selling price of chair model *j*	[EUR/unit]
q	price of EU ETS allowance	[EUR/t CO_2e]
R	daily turnover	[EUR/day]
R_i	target value assigned to goal constraint *i* in the general GP formulation	
w_{ik}^-	non-negative weights assigned to the negative deviation variables of goal constraint *i* at priority level *k* in the general GP formulation	
w_{ik}^+	non-negative weights assigned to the positive deviation variables of goal constraint *i* at priority level *k* in the general GP formulation	
x	vector of decision variables in the general LP formulation	
x_j	*j*-th decision variable in the general GP formulation	
x_1	daily production quantity of chair model M1	[units/day]
x_2	daily production quantity of chair model M2	[units/day]
x_3	daily production quantity of chair model M3	[units/day]

z	achievement function in the general GP formulation

Subscripts

D	daily
H	hourly
OTP	overtime premium
i	goal constraint index / chair model index
j	decision variable index / chair model index
k	priority level index

Superscripts

T	transpose operator
-	negative deviation
+	positive deviation

Abbreviations

BiH	Bosnia and Herzegovina
BSCI	Business Social Compliance Initiative
CGP	Chebyshev/minmax goal programming
CNC	computer numerical control
CO_2e	carbon dioxide equivalent
DM	decision-maker
ETS	emissions trading system

EU	European Union
EU ETS	European Union Emissions Trading System
FSC	Forest Stewardship Council
GP	goal programming
ISO	International Organization for Standardization
LGP	lexicographic goal programming
LP	linear programming
MCDM	multiple criteria decision making
OSHA	Occupational Safety and Health Administration
WGP	weighted goal programming

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DECLARATIONS

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AI usage

The author of the thesis, Ajla Piljević, used the following AI-tools during the preparation of the thesis:

1. ChatGPT
    a. Purpose of use: Grammar check
    b. Explanation of the use of the tool: Text was given to the tool to check if there are any grammatical or spelling mistakes.

Responsibility

The author, Ajla Piljević, takes full responsibility for the content of this thesis and has reviewed and edited the content generated by the possible use of AI tools.

1 Introduction

The wood industry is considered to be one of the traditional industries that constitute the foundations of the economy of Bosnia and Herzegovina (BiH). It is the only industrial branch that has consistently recorded a surplus in international trade. Characterised by exceptionally strong competition and a large number of companies, the wood industry has no identifiable market leader, so it is generally hard to stand out (Hadžić & Čavalić, 2022). In order to maintain their position in the market, companies should focus on innovative activities that can lead to improvements of existing processes and business operations.

Exports have been, and continue to be, key to the success of the furniture industry. The development strategy for the wood industry highlights the importance of continuously increasing exports of wood products in order to reduce the foreign trade deficit. A way to make this possible is by improving the production process so that companies can keep up with international demand (Muhić & Osmančević, 2022).

Given the dynamic nature of wood-processing companies, especially those manufacturing furniture, organising the production process is not an easy task. Engineering processes and management decisions can rarely be reduced to a single isolated criterion, as practical operations consistently require balancing conflicting priorities. Increasing production may result in higher labour costs, additional overtime, or elevated emission levels, which indicates that optimising only one criterion can negatively affect other important aspects of the production system. To ensure that everything runs smoothly, there needs to be good coordination of production quantities, inventory levels, workforce size, and the use of available resources to meet actual or forecast demand over a given planning horizon. With all of this in mind, effective production planning can be considered an important contributor to the operational performance of manufacturing companies (Guzman et al., 2022).

The application of goal programming (GP) appears to be a suitable approach for optimising the production planning of wood-processing companies to support their efficiency and competitiveness. Besides being an extension of linear programming (LP), goal programming is also considered a subset of multiple criteria decision making (MCDM), a subfield of operations research dealing with decision problems with multiple objectives. Therefore, GP is characterised by the ability to place multiple conflicting goals within a single model

(Schniederjans, 1995). Lexicographic goal programming (LGP), one of the most widely used GP variants, was selected as the optimisation approach applied in this master's thesis. It allows the decision-maker (DM) to assign different priority levels to each goal, after which it seeks a satisfactory solution that minimises unwanted deviations from the specified target levels while preserving the established priority hierarchy (Romero, 2001). This exact approach was used in this thesis for the company Wood Team d.o.o., a wood-processing company manufacturing dining chairs. Based on the planning horizon and aggregation, production planning problems can be solved with a long-term aggregated plan or a short-term detailed plan (Guzman et al., 2022). In this thesis, two models for daily production planning with the same goals but different priority structures were formulated so that, aside from testing the applicability of GP, the influence of different priority orders could also be analysed. The goals and their priority order were determined based on the preferences of the company director. The aim of the models is to identify a suitable production mix for the selected chairs while trying to achieve a specified profit, keeping indicative CO_2 emission costs within an acceptable level, reducing underproduction relative to average daily demand, and minimising underutilised labour capacity and overtime.

The research questions are: (1) does GP constitute a justifiable supporting tool for decision-making in production planning within a wood-processing company in BiH, (2) what possibilities and benefits does its use offer, and (3) how do different priority orders affect the resulting production mix. The contribution of the thesis is the development and case-based evaluation of two goal programming models for production planning in a wood-processing company in BiH. The two developed models jointly consider economic, operational and environmental goals within a single GP production model, and their comparison shows how managerial priorities affect the production mix and the distribution of goal deviations across departments.

The obtained results are thoroughly analysed and compared, and the models are further tested with a sensitivity analysis. Lastly, the main findings are summarised in the conclusion, together with suggestions for further development and possible improvement of the proposed approach.

2 Literature review

In this chapter, the theoretical and practical background of the relevant research is presented. It provides an overview of LP as the methodological foundation of GP, followed by a more detailed description of GP, its main characteristics and applications. The chapter also examines production planning challenges in the wood industry, establishing the relevance of applying GP in this context.

2.1 Linear programming

Linear programming is a mathematical optimisation method used in order to minimise or maximise a linear objective function while satisfying specified linear constraints. The constraints can be either equalities or inequalities within the unknowns (Goldfarb & Todd, 1989). A linear program consists of decision variables, the unknowns in the problem, an objective function which needs to be minimised or maximised, and lastly a set of constraints that need to be fulfilled when running the program (Shor, 2024).

According to Matoušek and Gärtner (2007), in a general linear program, the goal is to find a vector $x \in \mathbb{R}^n$ for which the objective function is minimised or maximised while the specified constraints are satisfied, where *n* is the number of decision variables. It can be written as follows:

$$\begin{aligned} &minimise\ or\ maximise\ c^T x \\ &\text{subject to } Ax \leq b \end{aligned} \tag{1}$$

where:

$x -$ vector of decision variables

$A -$ matrix of all the coefficients in the linear programming constraints

$c -$ vector of objective-function coefficients

$b -$ right-hand-side vector

T −transpose operator

Inequality constraints can be converted into equalities by introducing appropriate slack or surplus variables. The function that is targeted for the purpose of optimisation is called the objective function, and has the following form:

$$\boldsymbol{c}^T\boldsymbol{x} = c_1x_1 + \cdots + c_nx_n \tag{2}$$

where $\boldsymbol{c} \in \mathbb{R}^n$ is an already defined vector.

Although linear programming is a widely used optimisation method, Hillier and Lieberman (2001) describe that its application comes with some limitations. A linear program is based on the assumptions of proportionality and additivity, meaning that the contribution of each variable to the objective function and resource consumption has to be linear and independent of the values of other variables. Furthermore, all model coefficients are assumed to be known and constant. With these assumptions, the real production system is simplified, as it can often have nonlinear relationships and uncertain data. For this reason, the results of linear programming models may not fully reflect the real-world conditions.

The most significant restriction of linear programming is its limited ability to deal with problems which have multiple conflicting goals (Ignizio, 1985). This disadvantage later found its solution in goal programming.

2.2 Goal programming

According to Taha (2017), a traditional approach to operations research has long relied heavily on linear programming, which is focused only on optimising one specific goal, such as maximising profit or minimising costs. While linear programming offers mathematically precise results, its success has created a tendency to select it as a preferred modelling tool, even when it might not be the most suitable. This can lead to the formulation of a model that is too removed from the real situation, which makes the results hard to implement in a real industry setting that is far more complex.

Precisely from this need to handle goals with different, often conflicting, requirements that should be taken into consideration simultaneously, goal programming was developed as a more suitable approach that takes the conflicting objectives and converts them into goals

(Kaur et al., 2023). Goal programming was introduced by Charnes and Cooper back in 1961, which is when the term itself was used for the first time (Caballero et al., 2009). It marked an increase in popularity amongst researchers during the period of late 1970s and early 1980s (Tamiz et al., 1995). It has been described as one of the most widely used approaches in multiple criteria decision making (Colapinto et al., 2017). In these early stages of development and use, goal programming proved to be a useful tool in many different areas such as academic resource planning, portfolio analysis, engineering, manufacturing, finance, and many more. This intense interest in GP has led to the development of algorithms for resolving GP problems which are larger in scale, as well as special-case algorithms. Many published papers addressed errors of GP and explained that they could be avoided through the correct setting of weights, goals, and priority levels (Tamiz et al., 1995).

As described by Broz et al. (2019), standard goal programming models are based on deterministic goals and aspiration levels that are clearly and precisely specified, with a purpose of finding a satisfactory solution, rather than claiming that one alternative is universally best. For every goal, an aspiration level is defined by decision-makers, while the difference between the achieved and targeted values is represented using negative and positive deviation variables. The solution is judged by the extent to which those aspirations are missed. The negative deviation indicates the extent to which the goal is underachieved, while the positive deviation indicates the extent to which it is exceeded. Instead of directly maximising or minimising individual goals, goal programming minimises those deviations which the decision-makers deem unwanted.

Some versions of GP models made from the standard model are lexicographic (LGP) and weighted goal programming (WGP) (Colapinto et al., 2017). Kaur et al. (2023) explain that LGP is an approach in which a decision-maker determines a priority order of goals beforehand. This way, a goal with the highest assigned priority will be considered first, and only after the best possible solution has been found will the model move to the optimisation of the next. So, when a decision-maker is able to distinguish relevance between goals, is when the use of LGP would be helpful. WGP uses weighting coefficients in order to express different relative importance of individual goals, and all the goals are considered at the same time. By being placed within a single weighted and normalised achievement function, this version of GP allows direct compromises between the unwanted deviation variables.

Another variant of GP is the Chebyshev or minmax goal programming (CGP). This version seeks more balanced, less extreme solutions by using maximal deviations, which provide the balance between objective functions (Wang et al., 2021).

2.3 Application of goal programming in production planning of the wood and furniture industries

Broz et al. (2019) applied GP to daily production planning in the wood industry, focusing on the operation of sawmills. The research points out that production planning in this environment requires considering multiple conflicting criteria, which is why achieving one goal can negatively affect the achievement of others. The goals considered in the presented GP model were maximisation of profit, minimisation of raw material loss, minimisation of inventory, and minimisation of unsatisfied demand. With these goals, a mixed-integer linear programming model was developed, and the corresponding operational constraints regarding the available raw material, processing time, cutting patterns, and product demand were defined. The authors first optimised the defined goals individually in order to analyse the conflicts between them. The achievement of one goal did result in significantly worse values of the other goals. To resolve this, WGP and CGP were used within an extended goal programming approach. The results showed that selected preferences and GP approach affected the obtained results, with CGP achieving lower profits and generally poorer goal achievements than WGP. The model was additionally tested under a 25% increase in demand to examine how changes in demand influence the production planning results.

In the paper by Komsiyah et al. (2018), fuzzy goal programming was used for production planning of a furniture manufacturing company. The case study was conducted in the company CV. Arte Jaya. The model determined a production mix of five different products while trying to achieve profit maximisation, production cost minimisation and raw material cost minimisation. The model constraints included the available production time, warehouse capacity, the availability of different raw materials, as well as minimum and maximum production quantities. Like in the previous paper, the authors optimised each defined goal individually. This was done using linear programming, and the obtained results were compared with the aspiration levels defined by the company. Based on these values, a fuzzy goal programming model was formulated, in which the degree of satisfaction of the fuzzy

goals was maximised. The resulting production plan satisfied all aspiration levels for profit and costs set by the company.

Hisjam et al. (2015) applied GP to develop a sustainable partnership model for the supply chain of the wooden furniture industry. A wood supplier, a furniture manufacturer, and a buyer were all included in the model, as well as thirteen economic, social, and environmental goals. The defined hard constraints included production capacity, wood availability and consumption, production waste, and conditions related to additional prices paid by the buyer. The model was tested through a numerical trial based on observations of the export-oriented wooden furniture industry in Central Java. The authors analysed four scenarios in which different weights were assigned to the economic, social, and environmental goals. The results showed that assigning greater weights to social or environmental goals led to better achievement of almost all goals compared with assigning equal weights or placing greater emphasis solely on economic goals.

The described studies show the versatility of GP and its ability to address different decision-making problems in production planning and the wood and furniture industries. It can be observed that the reviewed studies treat production capacity as a hard constraint rather than a goal, so the utilisation of available working time cannot be adjusted in exchange for other model goals. An environmental goal is included only in the study by Hisjam et al. (2015), while Broz et al. (2019) and Komsiyah et al. (2018) are only focused on economic, material and demand-related goals. Finally, none of the presented models has a pre-emptive priority structure, so the effect of the priority order has not been analysed. This constitutes the research gap addressed by this thesis. Two mixed-integer lexicographic models that share the same goals but differ in priority order, where underutilised labour capacity, overtime and CO_2 emission costs, together with target profit and demand, are formulated as goals within a single model, address that gap and provide an indication of the applicability of GP in the wood industry of BiH.

2.4 Production planning challenges in the wood industry of Bosnia and Herzegovina

The wood industry, an important segment of the economy of the Federation of Bosnia and Herzegovina, represents an excellent sector for the implementation of goal programming. It is the Federation's oldest industrial branch, has a long-lasting tradition, and is also described as ecologically acceptable. Improved production planning can be viewed as one of the operational measures that may contribute to strengthening the wood sector as predominantly export-oriented, which could prove to be beneficial in the development of the manufacturing industry of the Federation of Bosnia and Herzegovina (Federalno ministarstvo energije, rudarstva i industrije i Privredna/Gospodarska komora Federacije Bosne i Hercegovine, 2018).

With the wood sector being oriented towards exports, working on the optimisation of production planning in wood-processing companies is of high value, as it could further help with maintaining competitiveness in demanding international markets.

The Strategy for the Development of the Wood Industry of the Federation of Bosnia and Herzegovina for the Period 2016-2025 also identified a few production-related problems. Installed sawmilling capacity was estimated to be at least twice as high as the permitted annual timber harvest. General-purpose machines dominate in many production facilities, the number of automated production lines and machining centres is insufficient, and upholstered furniture production largely relies on manual labour. Future investments should be oriented towards modernising existing production facilities, better use of available capacities and increasing the production of final products. The use of wood waste, biomass and lower-quality wood for producing energy, pellets and briquettes is mentioned as having considerable potential (Federalno ministarstvo energije, rudarstva i industrije i Privredna/Gospodarska komora Federacije Bosne i Hercegovine, 2018).

Based on the analysis conducted by Šipragić (2022), data from 2020 show that the wood processing industry of BiH consisted of 1,348 companies and employed more than 25,000 workers, while the total value of sales was EUR 1.03 billion and the total export value EUR 576 million. It is worth mentioning that the export value of furniture was 40% higher on average during 2016-2020 than that of wood and wooden products. Despite this

performance, companies were dealing with an unstable supply of raw materials, insufficient capacity utilisation, a shortage of qualified workforce, and they were in need of production process improvements. A survey conducted among 20 wood-processing companies in BiH, one of which was also Wood Team d.o.o. Ilijaš, further supports these claims and shows that most of the surveyed companies expressed interest in training in lean production and process optimisation, development of higher value-added products, and business digitalisation (Šipragić, 2022). These findings indicate that the improvement of the wood processing industry in BiH should involve not only purchasing new machinery but also comprehensively modernising the production system.

Šipragić (2022) also identifies the growing importance of eco-friendly furniture based on eco-design and circular-economy principles. The report states that the trend of decarbonisation highlights the increasing use of wood in construction. With this in mind, companies should also start considering environmental goals when thinking about optimisation and improvements, not just economic and operational goals. This further supports the relevance of GP, since it enables several different goals to be considered within one production planning model.

3 Case company: Wood Team d.o.o.

The case company that has contributed to the preparation of this master's thesis by providing valuable information and data is Wood Team d.o.o. This chapter gives an overview of the company and its production processes. The description is based on the information available on the official company website (Wood Team d.o.o., n.d.) as well as information received through discussions with the company director.

3.1 Company overview

Wood Team d.o.o. is a dining chair manufacturer based in Bosnia and Herzegovina. According to the company's official website, it has operated in the wood-processing field since 2010 and manufactures chairs which are aimed at furniture retailers, procurement teams, large retail chains, and private-label programmes. The company runs four specialised plants in Bosnia and Herzegovina which help it carry out every stage of dining chair production internally. Across these plants, operations include sawmilling and drying, plywood and veneer, machining, assembly, upholstery, finishing, and logistics. Wood Team operates according to certification and compliance framework related to timber traceability, quality management, and social compliance, including Forest Stewardship Council (FSC) chain-of-custody, ISO 9001, and Business Social Compliance Initiative (BSCI), respectively. These are all particularly relevant for companies which are supplying international retail and procurement networks (Wood Team d.o.o., n.d.).

Wood Team's product portfolio can be grouped into solid wood chairs, upholstered chairs, and chairs with metal components. Solid wood chairs are mainly produced from European oak and beech using traditional joinery techniques, with additional reinforcement where required by design, followed by in-house surface finishing. Besides producing wooden parts, Wood Team also produces its own metal parts. Any chair model can be made with metal parts as well, which are formed, welded, and finished in its metal shop in Visoko. The upholstery of the wooden or metal frames is done with customer-selected or customer-supplied fabrics that are cut and sewn in the company's own workshop. The high quality of

the end product the company also attributes to a very skilled workforce. Only the most experienced upholsterers, finishers, and machinists are hired, with the next generation of skilled professionals being trained in-house (Wood Team d.o.o., n.d.). Figure 1 presents the chair model “Almada”, one of many designs with wooden parts that the company has to offer.

Figure 1. Chair model "Almada"

In order to keep up with the competition, the company regularly updates its machinery on plant floors, so each year new modern industrial equipment is introduced (Wood Team d.o.o., n.d.). Figure 2 shows an example of a new computer numerical control (CNC) machining centre, which allows simultaneous automated machining of multiple wooden components with complex geometries.

Figure 2. Newly acquired CNC machine in the machining department

However, conventional machines and manual work remain necessary for operations that require flexibility and individual adjustment.

3.2 Production process

The first production stage takes place at the plant in Ilijaš, where raw timber from Bosnia and regional forests is processed. Controlling its own sawmill and drying kilns gives the company the ability to regulate lumber moisture content before the material goes onto further production stages. The production of plywood and veneer takes place in the Breza plant. There, curved components, seat shells, and backrests are made. Since the company produces its own chair parts, it does not depend on external suppliers and can quickly respond to design changes during product development (Wood Team d.o.o., n.d.). Figure 3 shows some of these components stored in its own warehouse, ready for the next processing steps.

Figure 3. Prepared wooden chair components awaiting further processing

Plants in Visoko and Zenica represent the main chair manufacturing facilities. Both of them handle machining, assembly, sewing, upholstery, finishing, packaging, and truck loading. By running two production plants at the same time, the company can process large catalogue programs and made-to-order runs in parallel, while reducing the risk of production delays between different orders (Wood Team d.o.o., n.d.). All the pictures presented in this thesis were taken at the plant in Visoko (Figure 4).

Figure 4. Plant in Visoko

The machining department is responsible for machining wooden components to the dimensions and shapes specified in the technical documentation of the product. Depending on the model of the chair, cutting to the required dimensions, planing, profiling or milling, drilling and sanding can be performed. The required processing sequence depends on the material, geometry and position of the component in the finished chair. Figure 5 shows the machining of chair components using conventional woodworking equipment.

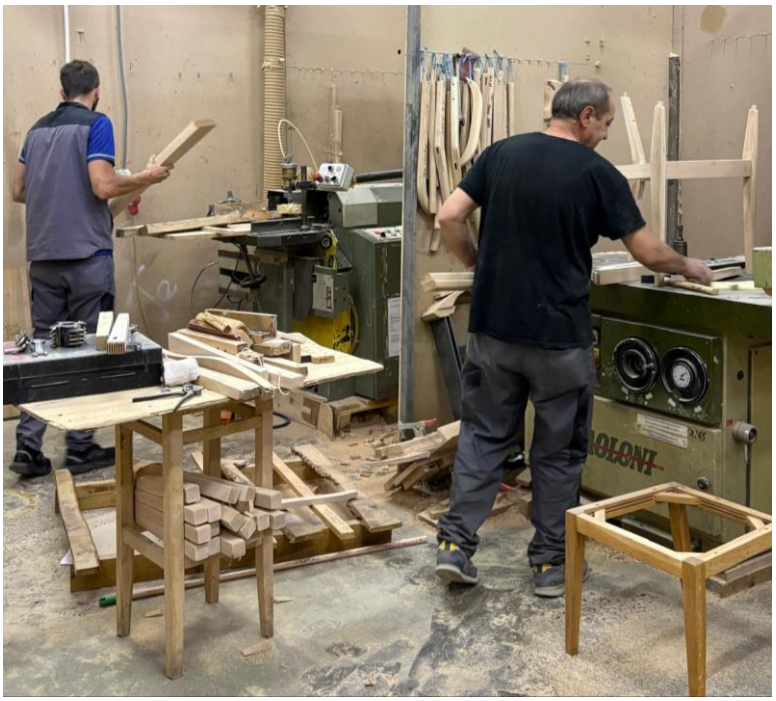

Figure 5. Machining of chair components

After the machining department, the wooden components go through finishing operations. These include additional sanding, staining, painting and varnishing, followed by drying. The exact procedure depends on the specific chair model, the type of wood and the customer's requirements. The upholstery process consists of preparing the upholstery materials and their attachment to the appropriate chair components. The upholstery covers are prepared in the sewing department beforehand, after which they are placed over the foam and secured onto the supporting structure. The material is then carefully stretched so that the finished surface is smooth and without visible wrinkles. Although some of these operations can be performed using machines, the final positioning and tensioning still mainly depend on manual work

and employee experience. The process of attaching the upholstery material to a prepared chair component can be seen in Figure 6.

Figure 6. Upholstery of a chair component

The separately prepared components are combined in the assembly department. This phase can include joining the wooden frame, legs, seat, backrests and upholstered elements into the final chair structure. An example of the assembly of a chair model can be seen in Figure 7. Precise positioning of all the parts during this phase is extremely important as incorrect alignment may affect the stability and appearance of the finished chair.

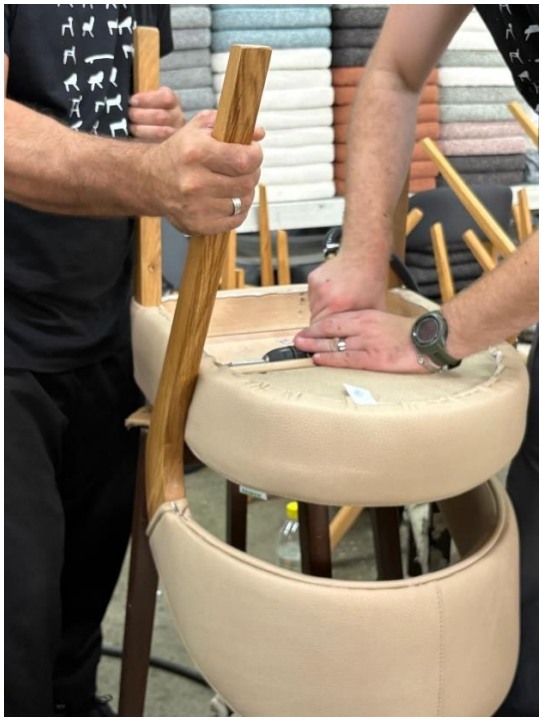

Figure 7. Assembly of an upholstered chair with wooden frame

Quality control is conducted during the whole process, and again at the end. Dimensions and joint quality are checked while the components are moving between production operations. Before packing, a final inspection is performed, which includes visual quality, structural integrity, and conformity to the approved sample (Wood Team d.o.o., n.d.). Chairs that meet all the requirements are packed and shipped to customers (Figure 8).

Figure 8. Chair packing for shipment

Even though the production process is described as a sequence of successive stages, all the operations are not linear. The schematic presentation of the overall process is shown in Figure 9.

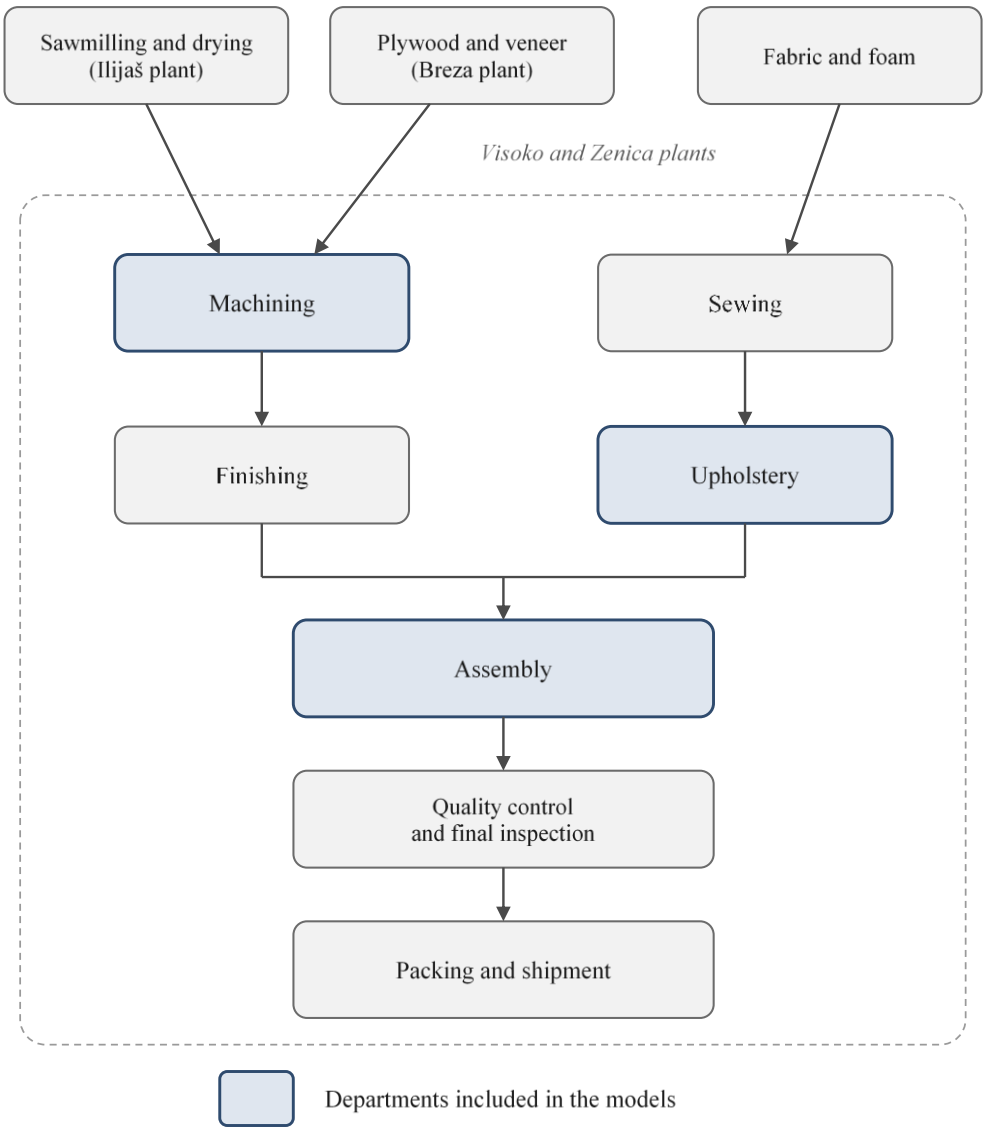

Figure 9. Schematic presentation of the production process

The wooden and upholstered components are prepared in parallel, after which they are combined during assembly. This requires suitable coordination between departments, since differences in processing times can cause components to accumulate between stages or leave particular departments temporarily underutilised.

4 Methodology and model formulation

In this chapter, a detailed methodology used to develop and solve two goal programming models is given. It describes the model scope, input data, assumptions, decision and deviation variables, goal constraints, priority structures, and solution procedure. The purpose of the described models is to demonstrate how goal programming can be applied in the daily production planning in a wood-processing company by simultaneously considering economic, operational and environmental goals.

4.1 Model scope and selection of the daily planning horizon

In production planning, based on chosen time horizons, three different plan types can be distinguished: long-range plans, medium-range plans, and short-range plans. While aggregate production planning, typically used in the medium-range plans, provides a rough estimation of quantities and timing of production, a short-term plan takes a more detailed approach, turning rough quantities into more specific data. With a short-term plan, it is possible to create a schedule with start and finish times, assignments of each machine and employee, necessary resources, and all other important information (Zanella & Vaz, 2023).

In order to examine the applicability of goal programming for the optimisation of production planning in the wood-processing company Wood Team d.o.o., two models with five goals were formulated. Both models are based on the same production data provided by the company, the same decision variables, and the same goal constraints. The difference between the models is the order in which the defined goals are prioritised. In consultation with the company's director, it was decided that the main focus should be on profit, labour underutilisation, CO2 emissions, overtime control, and meeting the average daily demand.

The models were developed as short-term daily production-planning models for selected chair models. The chosen horizon is aligned with the data provided by the company, the company’s managerial decision-making practice, and how the company analyses its own production. The available working time is expressed in minutes per worker per day, and both the satisfactory revenue and the average daily demand are expressed on a daily basis. Within

the broader scope of short-term production planning, the models were limited to determining daily production quantities. By determining the suitable production quantities of chosen products for the day, the results of the models can show how the quantities affect each individual goal. This way, possible capacity imbalances and areas requiring managerial attention can be identified, and with that, the company can consider suitable responses within its production planning process.

4.2 Comparative approach of two model variants

The approach of creating two models with differently prioritised goals was used because the final solution of a lexicographic goal programming model strongly depends on the order of priorities. Lexicographic minimisation of the achievement function will always favour deviation variables in higher-priority level goals and treat them as significantly more important than deviation variables in lower priority levels. It is expected that the two models may lead to different results, so their comparison can make it possible to observe how different managerial preferences influence the final production plan (Jones & Tamiz, 2010).

The goals and priority structures of the models can be seen in Table 1. In Model 1, the highest priority is achieving a target profit, followed by maintaining maximum acceptable CO_2 emission costs, minimising underutilised labour capacity, meeting average daily demand, and minimising overtime. Model 2 keeps profit and CO_2 emission costs as the two most important priorities, but gives greater importance to meeting the daily chair demand and overtime control before minimising underutilised labour capacity. Model 1 assigns a higher priority to the utilisation of labour capacity, while Model 2 places greater emphasis on meeting demand and limiting overtime. The purpose of the second model is not to correct the first model, but to test how the production plan would change when the same planning problem is evaluated through a different priority structure.

Table 1. Priority order in the two formulated models

Priority level	Model 1	Model 2
P1	Reaching the target daily profit	Reaching the target daily profit
P2	Minimising the CO_2 emission cost exceeding the maximum acceptable level	Minimising the CO_2 emission cost exceeding the maximum acceptable level
P3	Minimising underutilised labour capacity across the observed production departments	Minimising underproduction relative to the average daily demand
P4	Minimising underproduction relative to the average daily demand	Minimising overtime across the observed production departments
P5	Minimising overtime across the observed production departments	Minimising underutilised labour capacity across the observed production departments

4.3 Justification of model goals

All the goals and priority structures were defined together with the company's director, as the person with the authority over production planning decisions in the company. Several meetings were held in person in the Visoko plant, during which the production process was also observed directly. The most relevant aspects for daily production planning were first identified, followed by defining the target values on the basis of company-provided data. Lastly, the director was asked to rank the identified goals based on their importance, resulting in the priority structure of Model 1. The priority order of Model 2 was formulated by the author as an alternative in order to test the impact on the resulting plan. The following subsections explain why each goal was included in the two models.

4.3.1 Profit

In consultation with the company's director, it was agreed that reaching a specific profit target is the most important goal. Therefore, it is placed as the first priority goal in both models. By doing so, the lexicographic nature of the goal programming model will ensure

that the deviations from the profit target are always considered before any other goal. Furthermore, improvements within the rest of the goals will not be made at the cost of falling below the target profit.

4.3.2 CO_2 emission costs

Bosnia and Herzegovina is increasingly expected to align its climate-related policies with the European Union's regulatory framework. According to the EU Recommendations, the country should focus on trading and monitoring of emissions, as well as reporting and verification (European Commission, 2020). The need to introduce a credible carbon pricing system in Bosnia and Herzegovina is also emphasised by the Energy Community Secretariat. Discussions are already taking place regarding possible future models, such as a regional emissions trading system (ETS), a fixed-price ETS, a carbon tax, and integration into the European Union Emissions Trading System (EU ETS) (Energy Community Secretariat, 2025). These developments further indicate that this region is gradually moving toward a formal treatment of emissions. To reflect this broader environmental direction, the second priority in both models includes estimated CO_2 emission costs as a planning indicator that reflects the growing importance of environmental considerations in production planning. The EU ETS allowance price is used as a shadow carbon price to express the CO_2 footprints of the products in monetary terms for production planning, and does not represent an actual cost which the company has to pay.

4.3.3 Average daily demand

To ensure that production follows actual market needs, it is helpful to try to keep the production plan balanced and efficient, since underproduction comes with its costs and risks. In order to achieve that, the goal focusing specifically on reducing underproduction relative to the average daily demand was included in the model. If the models were developed without this goal in mind, they could produce results for product quantities that improve, for example, profit and capacity utilisation, but fail to meet the demand that the company has. Consideration of this goal is likely to make the proposed production plan more realistic and

applicable, and reduce the risk of underproduction, unmet orders, or delays in satisfying customer demand. The average daily demand values used in the models were obtained directly from the company. Wood Team operates on the basis of long-term contracts, mainly with buyers from the European Union. The quantities of each chair model are therefore agreed for longer periods, and the corresponding daily quantities can be expressed as an average daily demand.

4.3.4 Underutilised labour capacity and overtime

The relevance of considering labour capacity utilisation is supported by a previous analysis of the wood industry in BiH. Šipragić (2022) identified the need for better capacity utilisation as one of the weak links in the middle of the wood-processing value chain. For this reason, it is appropriate to include underutilised labour capacity as a goal in a model which aims to aid the optimisation of production processes.

In this thesis, focusing on underutilised labour capacity is a managerial goal with the purpose of identifying in which departments underutilised labour capacity occurs, and trying to adjust the workload between the observed departments as best as possible. It is considered a priority because it represents paid capacity which is not used in the production of the selected group of products. As presented in the description of the production process of Wood Team, the manufacturing of any type of chair involves labour-intensive, time-consuming processes, and time is a limited resource. If one department is underutilised and another simultaneously goes into overtime, this suggests that the selected production mix is not well aligned with the available capacities of the observed departments. This also ties to the importance of including both underutilised labour capacity and overtime within one model. Considering both goals allows the model to search for a production plan which would make better use of available working hours, without transferring workload to overtime.

Overtime is not just a financial cost; it also affects productivity, errors and safety. In a paper published by the International Labour Office, it is stated that although overtime increases production levels per worker, the overall hourly productivity drops. A study of 18 manufacturing industries in the United States found that, when overtime increases by 10%, there is a 2.4% decrease in hourly productivity (Golden, 2012). Furthermore, the

Occupational Safety and Health Administration (OSHA) indicates that fatigue increases the risk of illness and injury, and that a 12-hour daily shift is linked to a 37% higher risk of injuries (Occupational Safety and Health Administration [OSHA], n.d.).

4.4 Model assumptions

The models were developed based on the assumptions presented below, which define the boundaries within which the results should be interpreted. The assumptions are as follows:

- Only the three selected chair models are included in the optimisation model. As the best-selling models, they are treated as the representative product group of the observed production system. The models therefore do not represent the company's entire production assortment.
- In the model formulation, the full available capacity of each observed department is assumed to be available for the production of the selected group of products. Time needed for the production of other products from the company's assortment is outside the scope of the model.
- Processing times of chair models in each department are treated as fixed input parameters.
- The planning period is limited to one working day with 480 available working minutes per worker, as provided by the company.
- In the models, an average daily demand is used as a target value for the single working day that is considered. However, this does not mean that the demand under real business conditions is permanently constant. Seasonality is not considered in the models.
- Break times are not deducted from the labour capacity because the current version of the model is not focused on detailed scheduling of shifts. It is focused on daily production quantities and department capacity.
- Full availability of the planned workforce is assumed for the observed day, and short-term variations caused by employee absences are not included in the models.

- It is assumed that there is a sufficient amount of materials needed for the production of selected chair models. Material availability and inventory levels are not added as model constraints.
- The CO_2 footprint values used in the model were provided by the company and are treated as input parameters for the environmental goal.
- The EU ETS allowance price is used only as a proxy carbon price for converting the provided CO_2 footprint values into a monetary planning indicator. It is not assumed that the company is directly regulated under the EU ETS.
- As wage data for each department were not available, an equal average wage cost per worker was assumed across the three observed departments.
- The focus of the model is on reducing underproduction. According to the company, unmet demand results in real costs for the company, consisting of a contractual penalty and the lost profit per unit. Overproduction does not generate such costs, as the company has available storage capacities and can sell the surplus chairs to other customers. These costs are not quantified in the model, but they justify treating underproduction and overproduction differently.

Assigning the full available capacity of each observed department to the three selected chair models creates an upper-bound capacity scenario for this product group. In normal operations, other products may compete for the same workers and department time. Thus, the solutions should be interpreted as planning recommendations under these assumptions.

4.5 Decision variables and notations

The decision variables of the model are defined as follows:

x_1 – daily production quantity of chair model M1,

x_2 – daily production quantity of chair model M2,

x_3 – daily production quantity of chair model M3.

For each goal constraint, negative and positive deviation variables are introduced. The negative deviation d_i^- shows how much the achieved value falls short of the ith target, while the positive deviation variable d_i^+ shows how much the achieved value goes above the ith

target. The exact meaning of each deviation depends on the goal being formulated and is demonstrated in Table 2.

Table 2. Deviation variables for different goals

Deviation variable	Meaning
d_1^-	negative deviation from the target daily profit
d_1^+	positive deviation from the target daily profit
d_2^-	the amount by which the daily CO_2 emission cost falls below the maximum acceptable level
d_2^+	the amount by which the daily CO_2 emission cost exceeds the maximum acceptable level
d_3^-, d_4^-, d_5^-	underutilised labour capacity in the machining, upholstery, and assembly departments, respectively
d_3^+, d_4^+, d_5^+	overtime in the machining, upholstery, and assembly departments, respectively
d_6^-, d_7^-, d_8^-	production shortfall for chair models M1, M2, and M3, respectively
d_6^+, d_7^+, d_8^+	production surplus for chair models M1, M2, and M3, respectively

4.6 Input data and formulation of goal constraints

The following pages present data from the company used in both models. The selected chair models are denoted as M1, M2, and M3.

4.6.1 Selling prices and estimated unit profit

Based on data received from the company, the satisfactory daily revenue is EUR 10,400. The selling prices of each chair model can be seen in Table 3. With the given margin of 10%, the corresponding unit profit for chair models are calculated, as well as the target daily profit of EUR 1,040 that needs to be met.

Table 3. Selling prices and estimated unit profit of the selected chair models

Chair model	Selling price (EUR/unit)	Profit margin	Unit profit (EUR/unit)
M_1	63.50	10%	6.35
M_2	72.00	10%	7.20
M_3	81.50	10%	8.15

If the company were to produce quantities equal to the average daily demand, the achieved profit would be EUR 891.74 per day, which is approximately 14% less than the target daily profit. In order to preserve a satisfactory profit level after applying the indicative CO_2 emission costs and the potential overtime costs, the target daily profit of EUR 1,040 is deliberately set above EUR 891.74, as it represents an aspirational level of the company. The model is driven towards production above the average daily demand, which is achievable with the available capacities, as producing only the average daily demand leaves a part of the available department capacity unused.

When formulating the constraint for the goal of reaching the target daily profit of EUR 1,040, the additional cost of overtime is also considered in the equation. For the estimation of the costs of overtime, a structure of costs provided by the company was used. Based on these data, approximately 45% of turnover is allocated to material costs, 30% to wage costs, and 15% to other fixed costs, while the remaining 10% represents the profit margin. Daily turnover for the observed chair models is estimated based on their average daily demand and selling prices:

$$R = \sum_{j=1}^{3} D_j P_j \tag{3}$$

where:

R – daily turnover

D_j – average daily demand

P_j – selling price of chair model j.

The average daily demand for each chair model is:

$$D1 = 56.9, \qquad D2 = 37.9, \qquad D3 = 31.6 \tag{4}$$

Using the presented data, the estimated daily turnover is:

$$R = 8917.35\ \frac{EUR}{day} \tag{5}$$

The estimated total daily wage cost is:

$$0.3 \times 8917.35 = 2675.205\ \frac{EUR}{day} \tag{6}$$

The total number of workers in the three observed departments is 48. Given the fact that the wage data for each department were not available, the estimated total daily wage cost was divided equally among the 48 workers:

$$c_D = \frac{2675.21}{48} = 55.73\ \frac{EUR}{worker} \tag{7}$$

where:

c_D – estimated daily wage cost per worker

For an eight-hour shift, the average cost for an hour of work is:

$$c_H = \frac{55.73}{8} = 6.97\ \frac{EUR}{h} \tag{8}$$

where:

c_H – average hourly labour cost

Based on the information given by the company director, overtime is paid at a rate 30% higher than the regular hourly rate. Since the regular labour cost is already included in the profit values of each chair, only the additional 30% overtime premium is deducted from the profit:

$$c_{OTP} = 0.30 \times 6.97 = 2.09\ \frac{EUR}{h} \tag{9}$$

where:

c_{OTP} – additional overtime premium

Given that the capacity-deviation variables are expressed in minutes, the additional cost per minute is:

$$c_{OTP} = \frac{2.09}{60} = 0.03483\ \frac{EUR}{min} \tag{10}$$

The total daily profit, with the consideration of additional overtime cost per each department can be written as follows:

$$P = 6.35x_1 + 7.20x_2 + 8.15x_3 - 0.03483(d_3^+ + d_4^+ + d_5^+) \tag{11}$$

where:

$P -$ total daily profit

The goal constraint for reaching the target daily profit of EUR 1,040 is:

$$6.35x_1 + 7.2x_2 + 8.15x_3 - 0.03483(d_3^+ + d_4^+ + d_5^+) + d_1^- - d_1^+ = 1040 \tag{12}$$

4.6.2 CO_2 footprint and emission cost data

The second priority of both models is to limit the estimated daily costs of CO_2 emissions. The calculated values of CO_2 footprint of each chair model were provided by the company. In order for CO_2 emissions to be included in the model together with economic and production-related goals, the carbon footprint of each chair model was converted into an estimated cost of emission per product unit. For the purpose of this conversion, the EU Emissions Trading System was used as a reference for determining the costs of carbon emissions. Wood Team d.o.o. is not covered by the EU ETS, nor does the company pay these emission allowances.

The EU ETS is one of the world's largest carbon markets with the purpose of reducing the overall EU emissions (European Commission, 2026). Carbon markets are an increasingly used instrument for regulating carbon emissions. By making polluters pay for carbon emissions, pollution becomes undesirable for companies. The basis of this carbon market is a cap-and-trade system, with the cap representing an allowed total amount of emissions determined by governments, and trades referring to the buying and selling of emission allowances. One emission allowance gives the right to emit one tonne of CO_2 equivalent

(Bayer & Aklin, 2020). The EU ETS allowance price is market-based, therefore the price of one tonne of CO_2 equivalent is not constant. For this reason, the value of the price used in this thesis is only a reference value chosen at the beginning of the master's thesis writing. On April 22, 2026, the observed value was 75.43 EUR/t CO_2e, and this is the reference carbon price used in the calculations for the model (Trading Economics, 2026). The given CO_2 footprint expressed in kilograms was converted into tonnes by dividing it by 1000, and multiplied by the selected EU ETS allowance price. The following equation was used:

$$k_i = \frac{e_i \cdot q}{1000} \tag{13}$$

where:

k_i – costs of CO_2 emissions per unit of chair model *i*,

e_i – CO_2 footprint of chair model *i*,

q – price of EU ETS allowance.

The obtained results of these calculations can be seen in Table 4.

Table 4. CO_2 footprint and estimated emission cost per unit

Chair model	CO_2 footprint e_i (kg CO_2e/unit)	Emission costs k_i (EUR/unit)
M_1	12.50	0.9429
M_2	18.80	1.4181
M_3	27.80	2.0970

Using the average daily demand, the following equation was created:

$$B = k_1 D_1 + k_2 D_2 + k_3 D_3 \tag{14}$$

where:

B – daily CO_2 emission cost benchmark

The calculated value is:

$$B \approx 173.66 \frac{EUR}{day} \tag{15}$$

This is a modelled benchmark derived from the average daily demand, but for the purpose of the model, the calculated value is adopted as the maximum acceptable daily emissions cost.

The goal constraint for minimising the CO_2 emission cost exceeding the maximum acceptable level is:

$$0.9429x_1 + 1.4181x_2 + 2.097x_3 + d_2^- - d_2^+ = 173.66 \quad (16)$$

4.6.3 Labour capacity and processing time data

At Wood Team, many different departments make up the production process of every chair. In order to keep the goal programming model complex enough to include key components, and simple enough for interpretation and application, three important departments were considered, which are machining, upholstery and assembly. This choice is based on the consideration of the production process characteristics and information received from the company director. It was determined that these three departments represent the key departments, and the most labour-intensive stages of production. They account for the largest share of direct labour hours. In order to set the goal constraints, it is necessary to calculate the daily available working time of each department, and to present how much time is spent on each chair model per department. These data can be seen in Tables 5 and 6.

Table 5. Available daily working time per department

Department	Available working time per worker (min/day)	Number of workers	Available working time per department (min/day)
Machining	480	25	12000
Upholstery	480	20	9600
Assembly	480	3	1440

Table 6. Processing time per chair model and department

	Processing time per chair model (min/unit)		
Department	M1	M2	M3
Machining	69.8	85.6	107.3
Upholstery	57.5	71.2	86.8
Assembly	8.7	11.3	13.9

The goal constraints for labour capacity of each department are:

$$69.8x_1 + 85.6x_2 + 107.3x_3 + d_3^- - d_3^+ = 12000 \quad (17)$$

$$57.5x_1 + 71.2x_2 + 86.8x_3 + d_4^- - d_4^+ = 9600 \quad (18)$$

$$8.7x_1 + 11.3x_2 + 13.9x_3 + d_5^- - d_5^+ = 1440 \quad (19)$$

4.6.4 Average daily demand data

Table 7 shows the average daily demand that the company has, which the models seek to meet by reducing underproduction. In this goal, weights are assigned to the demand deviations that the achievement function is trying to minimise. Their importance is determined based on individual chair profits, so that the chairs with a higher unit profit are prioritised. This was selected as the weighting criteria because it directly expresses the economic consequences of not meeting the demand for a specific chair model. The weighted demand shortfalls are proportional to the profit lost from unmet demand. The weights therefore determine the relative importance of shortage between chair models rather than simply counting missing units. By dividing all the values by 6.35, the weight ratio is 1:1.1339:1.2835. These values were used in the calculations, while Table 7 presents rounded values to two decimal places.

Table 7. Average daily demand and demand-deviation weights

Chair model	Average daily demand (units/day)	Unit profit (EUR/unit)	Demand weight
M1	56.90	6.35	1.00
M2	37.90	7.20	1.13
M3	31.60	8.15	1.28

The goal constraints for the average daily demand of each chair model are:

$$x_1 + d_6^- - d_6^+ = 56.9 \tag{20}$$

$$x_2 + d_7^- - d_7^+ = 37.9 \tag{21}$$

$$x_3 + d_8^- - d_8^+ = 31.6 \tag{22}$$

4.7 General formulation of a GP model

A goal programming model represents a simplified mathematical depiction of an actual system. In this thesis, a weighted pre-emptive goal programming model is used. Let *m* denote the number of goal constraints, *l* the number of decision variables, and *K* the number of priority levels. Based on general formulations presented by Ekezie and Onuoha (2013) and Lakshmi et al. (2021), the model is formulated as follows:

$$\min z = \sum_{k=1}^{K} P_k \left[\sum_{i=1}^{m} (w_{ik}^- d_i^- + w_{ik}^+ d_i^+) \right] \tag{23}$$

Subject to:

$$\sum_{j=1}^{l} c_{ij} x_j + d_i^- - d_i^+ = R_i, \qquad \mathrm{i} = 1, 2, \dots, \mathrm{m} \tag{24}$$

$$d_i^-, d_i^+, x_j \geq 0, \mathrm{i} = 1, 2, \dots, \mathrm{m};\ \mathrm{j} = 1, 2, \dots, \mathrm{l} \tag{25}$$

$$P_1 \gg P_2 \gg \cdots \gg P_K \tag{26}$$

where:

$z -$ achievement function of the goal programming model;

P_k – k-th priority level in the pre-emptive hierarchy ($P_1 \gg P_2 \ldots \gg P_K$);

d_i^-, d_i^+ –negative and positive deviation variables;

w_{ik}^-, w_{ik}^+- non-negative weights assigned to the negative and positive deviation variables of goal constraint *i* at priority level *k*;

c_{ij}- coefficient of decision variable x_j in the *i*-th goal constraint;

x_j- *j*-th decision variable;

R_i – target value assigned to goal constraint *i*;

Depending on each individual goal, only the undesirable deviation variables may be included in the achievement function.

4.8 Mathematical formulation of both models

The complete mathematical formulation of the goal programming Model 1 is as follows:

$$\min z = P_1 d_1^- + P_2 d_2^+ + P_3(d_3^- + d_4^- + d_5^-) + P_4(d_6^- + 1.1339 d_7^- + 1.2835 d_8^-) + P_5(d_3^+ + d_4^+ + d_5^+)$$

Subject to:

$$6.35x_1 + 7.2x_2 + 8.15x_3 - 0.03483(d_3^+ + d_4^+ + d_5^+) + d_1^- - d_1^+ = 1040$$

$$0.9429x_1 + 1.4181x_2 + 2.097x_3 + d_2^- - d_2^+ = 173.66$$

$$69.8x_1 + 85.6x_2 + 107.3x_3 + d_3^- - d_3^+ = 12000$$

$$57.5x_1 + 71.2x_2 + 86.8x_3 + d_4^- - d_4^+ = 9600$$

$$8.7x_1 + 11.3x_2 + 13.9x_3 + d_5^- - d_5^+ = 1440$$

$$x_1 + d_6^- - d_6^+ = 56.9$$

$$x_2 + d_7^- - d_7^+ = 37.9$$

$$x_3 + d_8^- - d_8^+ = 31.6$$

$$x_1, x_2, x_3 \in \mathbb{Z}_{\geq 0}$$

$$d_1^-, d_1^+, d_2^-, d_2^+, d_3^-, d_3^+, d_4^-, d_4^+, d_5^-, d_5^+, d_6^-, d_6^+, d_7^-, d_7^+, d_8^-, d_8^+ \geq 0$$

The complete mathematical formulation of Model 2 with a different order of the same priorities is:

$$\min z = P_1 d_1^- + P_2 d_2^+ + P_3(d_6^- + 1.1339 d_7^- + 1.2835 d_8^-) + P_4(d_3^+ + d_4^+ + d_5^+) + P_5(d_3^- + d_4^- + d_5^-)$$

$$\text{Subject to: } 6.35x_1 + 7.2x_2 + 8.15x_3 - 0.03483(d_3^+ + d_4^+ + d_5^+) + d_1^- - d_1^+ = 1040$$

$$0.9429x_1 + 1.4181x_2 + 2.097x_3 + d_2^- - d_2^+ = 173.66$$

$$x_1 + d_6^- - d_6^+ = 56.9$$

$$x_2 + d_7^- - d_7^+ = 37.9$$

$$x_3 + d_8^- - d_8^+ = 31.6$$

$$69.8x_1 + 85.6x_2 + 107.3x_3 + d_3^- - d_3^+ = 12000$$

$$57.5x_1 + 71.2x_2 + 86.8x_3 + d_4^- - d_4^+ = 9600$$

$$8.7x_1 + 11.3x_2 + 13.9x_3 + d_5^- - d_5^+ = 1440$$

$$x_1, x_2, x_3 \in \mathbb{Z}_{\geq 0}$$

$$d_1^-, d_1^+, d_2^-, d_2^+, d_3^-, d_3^+, d_4^-, d_4^+, d_5^-, d_5^+, d_6^-, d_6^+, d_7^-, d_7^+, d_8^-, d_8^+ \geq 0$$

4.9 Solution procedure

The formulated goal constraints and achievement functions were implemented in Microsoft Excel, and the results were obtained using the Solver add-in. At each priority level, the corresponding achievement function was selected as the objective to be minimised, while the decision and deviation variables were specified as changing cells. Constraint equations of each goal were set so that the right-hand side was equal to the left-hand side, and the deviation and decision variables were required to be greater than or equal to zero. Since the models are determining the quantities of chairs to be produced in a day, integer restrictions were added for the variables x_1, x_2, x_3. These restrictions were only applied to the production quantities, while all other variables were allowed to have decimal values. The Simplex LP solving method was selected because all achievement functions and goal constraints in the

model are linear. Once the optimal value of the first-priority objective was determined, it was fixed as an additional constraint. This allowed the optimisation of the second-priority objective without any deterioration in the result achieved at the first priority level. This procedure reflects a pre-emptive lexicographic sequence, and it was repeated for all the following priority levels. The implementation of both models in Excel and the final solutions can be seen in Appendix 1, and an example of Solver settings for the final priority level of Model 1 can be seen in Appendix 2.

5 Results and Discussion

In order to evaluate and compare the results of the two optimisation models, a baseline scenario was defined to provide a common reference point. It was developed under the assumption that the daily production quantity of each chair model is equal to its average daily demand. The baseline scenario should not be understood as an actual representation of the company's production, but only as a calculated benchmark. The average daily demands of 56.9 units for M1, 37.9 units for M2, and 31.6 units for M3 result in a total of 126.4 chairs per day. Based on production quantities and the corresponding unit profits, the daily profit in the baseline scenario is EUR 891.74, and the estimated cost of CO_2 emissions is EUR 173.66. Given that the production corresponding to the average daily demand does not require any overtime, a final financial result of EUR 718.08 can be calculated. For the purpose of comparison in this thesis, the final financial result is defined as profit after the overtime premium cost and indicative CO_2 cost have been deducted. It is a model-based financial indicator, and not the real profit of the company. The baseline provides a common reference for evaluating how the optimised models affect total production and the final financial result, as well as for identifying the strengths and weaknesses of both models. Table 8 shows how the final financial results of both optimisation models, together with the baseline scenario, were formed. The optimal solution of Model 1 specifies a daily production of 163 chairs, which results in a final financial result of EUR 880.51. Model 2 produces four chairs fewer than Model 1 and achieves a slightly lower final financial result of EUR 867.72. Although Model 2 has lower overtime costs due to the higher priority assigned to overtime minimisation (EUR 9.1 compared to EUR 16.01 of Model 1), as well as a lower indicative CO_2 cost, Model 1 achieves a higher final financial result, which may be more attractive to the company. Regardless, both models have managed to achieve a higher estimated profit for the company compared to the baseline conditions.

Table 8. Breakdown of the final financial result

Indicator	Baseline	Model 1	Model 2
Total production (units/day)	126.40	163.00	159.00
Profit before overtime premium (EUR/day)	891.74	1070.10	1050.10
Overtime premium cost (EUR/day)	0.00	16.01	9.10
Profit after overtime premium (EUR/day)	891.74	1054.09	1041.00
Indicative CO_2 cost (EUR/day)	173.66	173.58	173.27
Final financial result (EUR/day)	718.08	880.51	867.72

The impacts of changing priority orders of the underproduction, overtime and underutilised labour capacity will be clearer by closely looking at each department. Table 9 gives an overview of how underutilised labour capacity and overtime are distributed across three observed departments.

Table 9. Distribution of underutilised labour capacity and overtime

	Baseline		Model 1		Model 2	
Department	Overtime	Underutilised labour capacity	Overtime	Underutilised labour capacity	Overtime	Underutilised labour capacity
Machining	0.00 h	23.22 h	0.62 h	0.00 h	0.00 h	2.16 h
Upholstery	0.00 h	14.78 h	5.63 h	0.00 h	3.27 h	0.00 h
Assembly	0.00 h	1.29 h	1.41 h	0.00 h	1.09 h	0.00 h
Total	0.00 h	39.30 h	7.66 h	0.00 h	4.36 h	2.16 h

Under the assumption of the model, producing quantities equal to the average daily demand leaves 39.3 hours of available departmental capacity unused for the selected group. By placing the goal to minimise underutilised labour capacity as the third most important priority, Model 1 was able to create a production mix so that the entire department capacities are used, resulting in 0 hours of underutilised labour capacity. This was achieved at the expense of the last priority in Model 1, which is overtime. It can be observed that, in order to produce 163 chairs in one day, not only is the full available capacity of each department required, but also longer working hours in all of them. Here, the upholstery department stands out the most, as it required significantly more overtime than the other two

departments. 5.63 hours are needed in the upholstery department, and only 0.62 hours and 1.41 hours in the machining and assembly departments, respectively. In contrast, Model 2 produces a less intensive capacity load, with 2.16 hours of underutilised labour capacity remaining in the machining department, and total overtime reduced to 4.36 hours. This means that Model 2 decreased overtime by approximately 43.1%. In this model, as well as in the first one, the upholstery department needs the most overtime in order to fulfil the needed production quantities, 3.27 hours to be exact, whereas the assembly department requires an additional 1.09 hours.

Figure 10 shows capacity relationships in relative terms, expressed as a percentage of each department's regular capacity. The total utilisation of available department capacities is represented by 100%. To make the relatively small differences between departments more visible, the range of the vertical axis was narrowed.

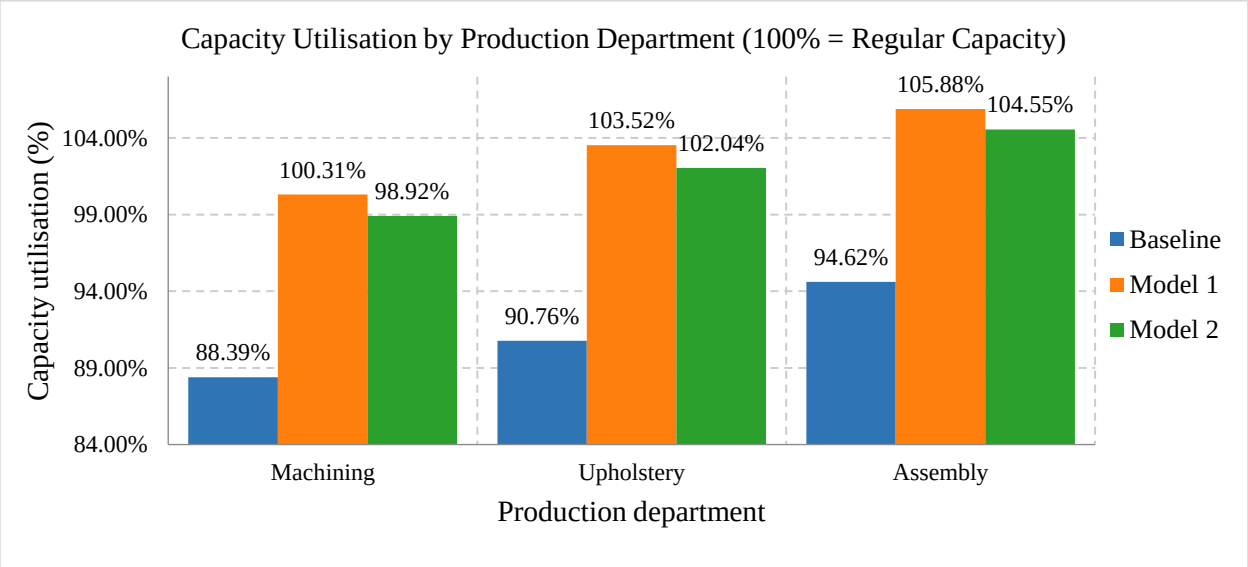

Figure 10. Department workload as a percentage of regular capacity

Even though the upholstery department requires the longest overtime out of all the departments in both models, it is actually the assembly department that has the highest relative exceedance from the regular capacity, where the utilisation accumulates to 105.88% for Model 1, and 104.55% for Model 2. This indicates that assembly is the most heavily loaded department in relative terms, while upholstery requires the greatest number of additional working hours. It also gives a clearer view of the described considerable amount

of unused capacity per department of the baseline scenario, compared to the two optimisation models.

The most significant characteristic of both models can be noticed by looking at how much of each chair model is being produced, compared to the average daily demand that the models are trying to meet. When comparing results between Model 1 and Model 2, presented in Table 10, the difference in produced quantities is not significant.

Table 10. Production quantities and deviations from average daily demand

Chair model	Average daily demand (units/day)	Model 1 production (units/day)	Deviation (units/day)	Model 2 production (units/day)	Deviation (units/day)
M1	56.90	124	+67.10	117	+60.10
M2	37.90	37	-0.90	37	-0.90
M3	31.60	2	-29.60	5	-26.60
Total	126.40	163	-	159	-
Total unweighted underproduction (units/day)	-	30.50	-	27.50	-
Weighted underproduction objective	-	39.01	-	35.16	-

Model 1 produces 124 units of chair model M1, while Model 2 produces seven units less. Model 2 produces three more units of chair model M3, while both models produce 37 units of model M2. It appears as though the models managed to create very similar production mixes, but no matter how small the difference in chair quantities of the two models is, it does result in a noticeable impact on labour utilisation and overtime, as previously demonstrated in Table 9.

The imbalance becomes evident when the production quantity of each chair model is compared with its average daily demand and when the production quantities of M1, M2, and M3 are compared within each optimisation model. A visual representation of this can be seen in Figure 11.

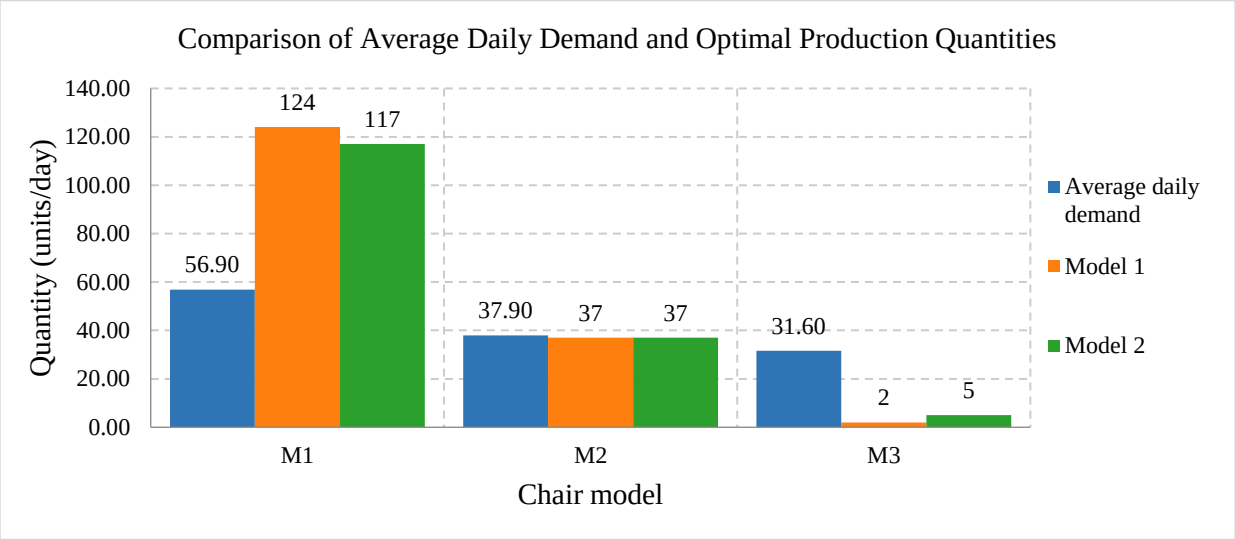

Figure 11. Comparison of average daily demand and optimal production quantities

The cause of this imbalance is directly tied to a combination of the impact of the priority hierarchy, unit profit, processing times and CO_2 emission costs. Even though the chair model M3 has the highest profit per unit, it also requires the most processing time in all three departments, and has the highest carbon footprint. This makes M3 less favourable when profit is considered in relation to processing time and CO_2 emissions. In contrast, model M1 has the lowest unit profit, but it is the fastest manufactured chair model with the lowest carbon footprint. For this reason, both models choose to produce the highest amounts of model M1, as it helps with achieving the first two priority goals. Model 1 prioritises the minimisation of underutilised labour capacity above the demand related goal, which is why the model further increases the production of model M1 in order to fill in the available working hours, even at the cost of a large exceedance with regard to the average daily demand. Since the minimisation of underproduction has more importance in Model 2, it did manage to slightly increase the production of model M3. However, given the pre-emptive structure, the improvement of lower priority goals cannot happen at the cost of already achieved results for profit and CO_2 emissions cost goals, meaning that a complete balance between chair models under the stated priority structure is difficult to achieve.

The practical feasibility of the resulting production mix should be interpreted with caution. As stated in Section 4.4, overproduction does not generate direct costs for the company, but this relies on the assumption that it can be placed on the market, and until then the surplus

remains in inventory as unsold output. The resulting mix should therefore be viewed as a mathematically optimal solution within the defined objectives and priorities and should be used as a guideline for management.

Table 10 also shows the weighted underproduction objective. The weighted values do not just show the number of missing chairs in relation to the average daily demand, they also take the economic importance of each chair model into consideration. This makes them indicators that give greater value to the shortfall of certain chair models. Model 2 produces a shortfall of 27.5 chairs, consisting of 0.9 units of M2 and 26.6 units of M3. Applying the respective weights gives a weighted underproduction objective of:

$$0.9(1.1339) + 26.6(1.2835) = 35.1616 \quad (27)$$

Because model M3 has the highest weight value, its shortfall contributes more heavily to the weighted objective. This demonstrates that the underproduction of models with a higher unit profit receives a greater penalty. The higher weighted underproduction objective in Model 1 indicates that it does not meet the average daily demand as well as Model 2. Even though weights show Solver how to treat the underproduction of each chair model, they still belong within the same priority goal, and Solver is minimising the weighted sum of underproduction deviations. Higher weight value of model M3 does not mean that its production will necessarily be closest to average daily demand, especially if it would worsen the achievement of higher-priority goals.

Figure 12 presents a visual representation of the deviations of optimal production quantities from average daily demand. The substantial overproduction of M1 is particularly noticeable. It is present because the target profit is EUR 1,040, which is approximately 16.6% higher than the baseline profit of EUR 891.74. The models must therefore increase production while avoiding an exceedance of the CO_2 emission cost benchmark. As previously described, chair model M1 is the most favourable for achieving both. In both models, the demand of model M2 is almost completely met. Highest deviations are present in the production of chair model M1, where the production exceeds the average daily demand by 67.1 units in Model 1, and 60.1 units in Model 2. The deviations in production of model M3 are slightly lower compared to model M1, with Model 1 missing 29.6 chairs, and Model 2 missing 26.6 chairs. It can be concluded that Model 2 achieves a slightly more balanced production structure, as it reduces the surplus of model M1, and the shortfall of M3.

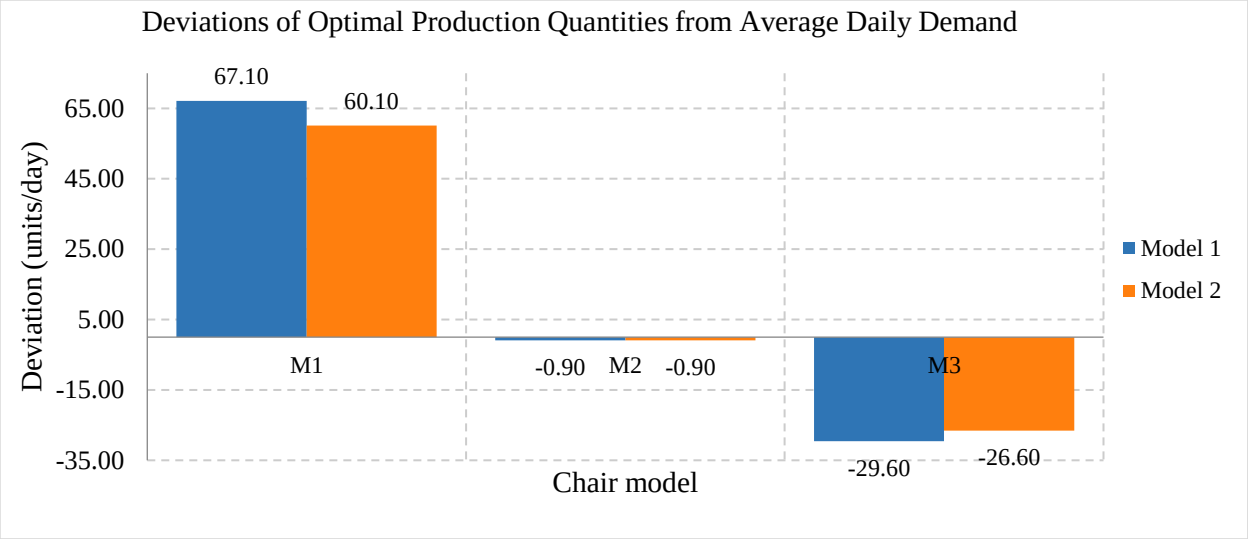

Figure 12. Deviations of optimal production quantities from average daily demand

Although the two models produce different results, the purpose of the comparison was not to determine which of them is better. As stated in Section 4.2, the second model was not formulated to correct the first one, but to test how the production plan changes when the same planning problem is evaluated through a different priority structure. Each model performs better on the goals placed higher in its own priority hierarchy, which confirms that the selected priority order directly shapes the resulting production plan. The choice between such structures is a managerial decision that depends on the preferences of the company.

5.1 Sensitivity analysis

Sensitivity analysis is used to examine how a quantitative model responds to changes made in the model inputs, and to obtain valuable information about its behaviour and structure (Borgonovo & Plischke, 2016). In order to see how changes in input parameters would affect the achievement of the defined goals, a sensitivity analysis was conducted for the two designed GP models. The capacity of the upholstery department was selected as the parameter to be changed for this analysis, as the previous results showed that it requires the most hours of overtime. This indicates that changes in its available capacity could have a significant impact on the production plan. Based on the initial data, the upholstery department has 20 workers, which corresponds to 9600 minutes of work per day. In the alternative scenarios the upholstery capacity was both reduced and increased by 480 minutes

per day, which represents a daily change of ±5% compared to the initial capacity of 9600 minutes. Table 11 shows the results of the sensitivity analysis for Model 1, and Table 12 for Model 2.

Table 11. Sensitivity analysis results for Model 1

Scenario	Upholstery capacity	M1/M2/M3	Weighted underproduction	Overtime	Underutilised labour capacity
19 workers	9120 min	126/38/0	40.56	16.06 h	0.00 h
20 workers	9600 min	124/37/2	39.01	7.66 h	0.00 h
21 workers	10080 min	136/32/0	47.25	5.92 h	0.00 h

Table 12. Sensitivity analysis results for Model 2

Scenario	Upholstery capacity	M1/M2/M3	Weighted underproduction	Overtime	Underutilised labour capacity
19 workers	9120 min	126/38/0	40.56	16.06 h	0.00 h
20 workers	9600 min	117/37/5	35.16	4.36 h	2.16 h
21 workers	10080 min	115/37/6	33.88	1.03 h	7.91 h

Decreasing the department capacity to 9120 minutes resulted in the same production mix in both models, which is 126 units of model M1, 38 units of model M2, and no units of model M3. The weighted underproduction is now 40.56, and the total overtime is 16.06 hours. Compared to the results of the initial models, there is a significant need for overtime, resulting in greater pressure on the remaining production capacity. As the chair model that takes the longest to manufacture across all three departments, and with the highest CO_2 emission cost, M3 is completely left out of the production mix. The fact that both of the models give the same results suggests that an absence of just one worker leaves less room for the differences in the ordering of lower-priority goals to influence the final production plan.

The scenario with 21 workers affects the two models differently. In Model 1, the production of M1 increases from 124 to 136, while there are five fewer M2 chairs, and no M3 chairs,

resulting in a weighted underproduction of 47.25. With one more worker, there is a decrease in overtime to 5.92 hours, and the underutilised labour capacity stays the same. This result can be explained by the structure of priorities, where the minimisation of underutilised labour capacity is more important than the minimisation of overtime and underproduction. The additional capacity reduces overtime but does not improve demand fulfilment, while the underutilised labour capacity stays zero.

Model 2 gives a slightly more balanced production mix with 115, 37, and 6 chairs of models M1, M2, and M3, respectively. This gives a lower weighted underproduction of 33.88, overtime decreases from 4.36 to 1.03 hours, and an increase of the underutilised labour capacity from 2.16 to 7.91 hours. This is also a direct result of the priority structure, in which underutilised labour capacity has the lowest priority.

Overall, the sensitivity analysis shows the importance of considering changes in the input parameters when applying GP in production planning. In real production conditions, the available capacity and all the other input data are not always constant, which is why the obtained results should not be treated as a fixed production plan. Instead, the GP model can be used as a flexible decision-support tool by rerunning it with updated input data as production conditions change.

6 Conclusions

The main contribution of this thesis is the formation and application of two GP models with economic, operational, and environmental goals to daily production planning of the company Wood Team d.o.o., using company-provided data and preferences of the company director. The results showed that GP can help in making better decisions for production planning, while simultaneously considering multiple conflicting goals. Both models achieved the target profit of EUR 1,040 while keeping the indicative CO_2 cost within the baseline level of EUR 173.66 per day, and both improved the final financial result compared to the baseline scenario of EUR 718.08 per day, reaching EUR 880.51 in Model 1 and EUR 867.72 in Model 2. The remaining goals related to underproduction, underutilisation and overtime were satisfied to different degrees depending on their assigned priority.

Testing the importance of the priority order by creating two models with the same goals but different priority structures gave an insight into how strongly the selected priorities can influence the results. This leads to the conclusion that companies should carefully consider not only which goals to include in the model, but also which of those goals matter most. At the same time, different priority structures can themselves be tested through GP, allowing decision-makers to compare their consequences before selecting the structure that best reflects the company's preferences. The sensitivity analysis further showed that changes in production conditions can affect the resulting production plan, while the different responses of the models highlighted the influence of the selected priority structure.

It is well known that daily product demands can vary between days, customers, orders, and seasons, and though the models presented in this thesis are designed as single-day planning models that do not take seasonality into consideration, these variations could still be indirectly reflected. A possible direction for the practical implementation of one of the two GP models is to use it within a rolling planning procedure. By updating the input parameters regularly, representative average daily demand values for specific time periods could be calculated, and with these new data, the model can then be rerun for each new planning cycle. This would allow the company to adjust the production plan according to the changing demand while keeping the structure of the goal programming models relatively simple and operationally applicable (de Sampaio et al., 2017).

GP can also be used for testing possible managerial decisions before their implementation. For example, before hiring new workers, it is possible to change the available capacity of different departments in order to analyse which department would most benefit from the addition to the workforce, and to see how this decision would affect the other goals.

A major advantage of a GP model is that it is very flexible and can be further developed to get even better results. In order to achieve greater control over the resulting production plan, limits can also be introduced for certain goals. If a company is unable to store an overproduced product, or if there is a maximum amount of overtime that the company is willing to allow, additional constraints could be added to the model so that it does not exceed the defined values. In this thesis, the models were kept sufficiently simple for interpretation and implementation, while still incorporating multiple priority levels, weighted deviations, and integer restrictions on the production quantities, making them mixed-integer lexicographic goal programming models with weighted achievement functions at selected priority levels.

That being said, the models have several limitations, the following being the most important: although the company produces a wide range of products, only three chair models were considered, all input parameters were treated as constant, full workforce and material availability were assumed, and overproduction was not penalised. The listed limitations also indicate some of the possible directions for future research, which could include demand uncertainty, both lower and upper demand boundaries, sharing capacity with other products, and including more products. If a more detailed model were to be developed, which would include many more products, departments, shifts, orders, and other operational factors, specialised optimisation tools like Gurobi and IBM CPLEX could be used for its implementation (Gurobi Optimization, n.d.; IBM, n.d.).

Overall, the results of this thesis demonstrate that goal programming is a valuable tool that can be used not only for production planning, but also for analysing the consequences of different priorities, production conditions and managerial decisions. Since effective production planning contributes to successful business operations, the flexibility of GP and its ability to consider multiple conflicting goals make it a valuable approach for improving production planning in wood-processing companies.

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Appendix 1. Excel implementation and final solutions for Model 1 and Model 2

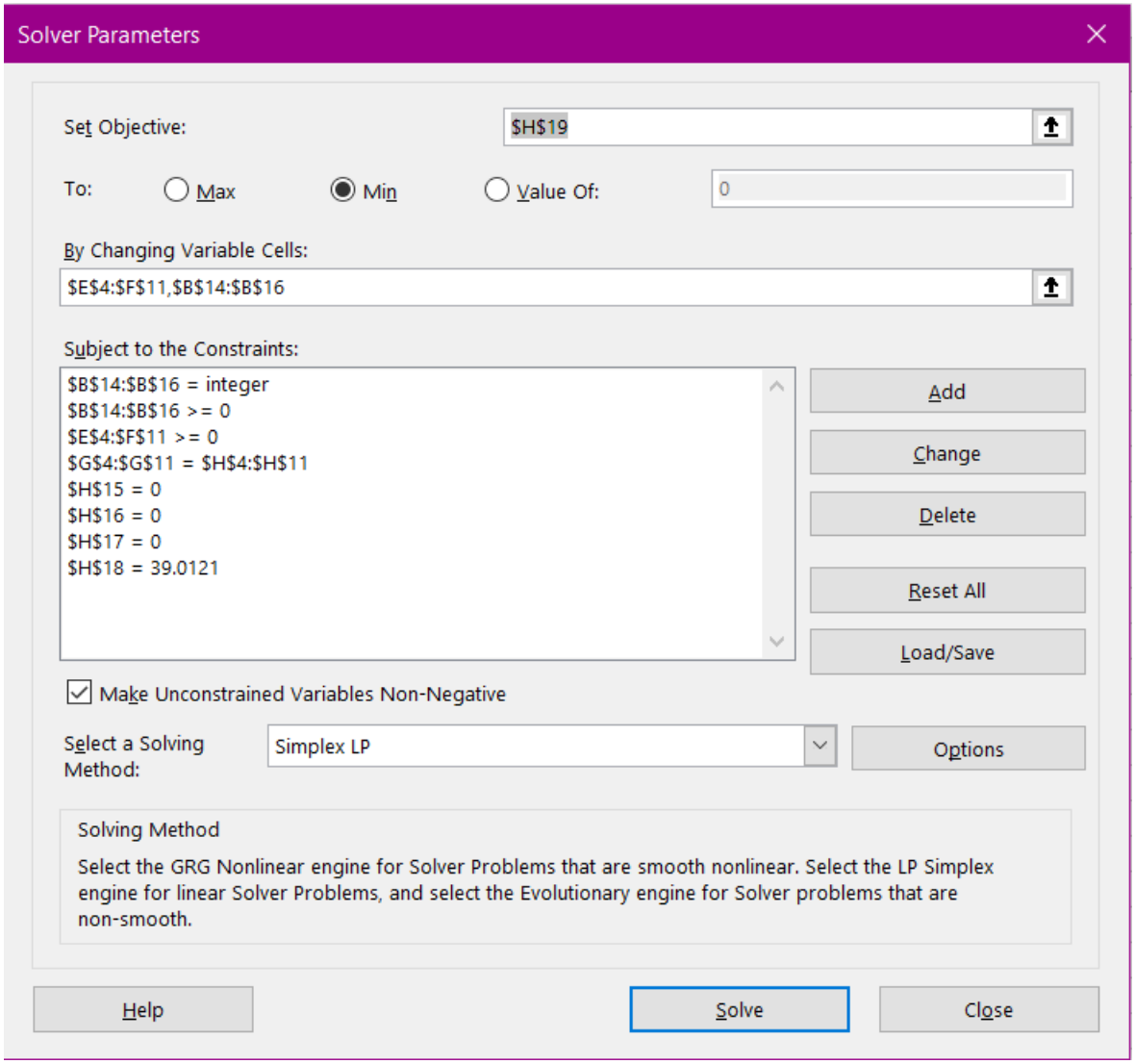
Model 1	Chair models			Deviation variables		Equations	
	M1	M2	M3	d-	d+	Left side	Right side
Profit per unit (EUR/unit)	6.35	7.20	8.15	0.00	14.09	1040.00	1040.00
CO2 emission cost per unit (EUR/unit)	0.94	1.42	2.10	0.08	0.00	173.66	173.66
Machining time (min/unit)	69.80	85.60	107.30	0.00	37.00	12000.00	12000.00
Upholstery time (min/unit)	57.50	71.20	86.80	0.00	338.00	9600.00	9600.00
Assembly time (min/unit)	8.70	11.30	13.90	0.00	84.70	1440.00	1440.00
Average daily demand for M1 (units/day)	1.00	0.00	0.00	0.00	67.10	56.90	56.90
Average daily demand for M2 (units/day)	0.00	1.00	0.00	0.90	0.00	37.90	37.90
Average daily demand for M3 (units/day)	0.00	0.00	1.00	29.60	0.00	31.60	31.60

x1	124
x2	37
x3	2

Objective values	
P1 profit	0.00
P2 CO2 emission cost	0.00
P3 unused labour capacity	0.00
P4 weighted underproduction	39.01
P5 overtime	459.70

Model 2	Chair models			Deviation variables		Equations	
	M1	M2	M3	d-	d+	Left side	Right side
Profit per unit (EUR/unit)	6.35	7.20	8.15	0.00	1.00	1040.00	1040.00
CO2 emission cost per unit (EUR/unit)	0.94	1.42	2.10	0.39	0.00	173.66	173.66
Average daily demand for M1 (units/day)	1.00	0.00	0.00	0.00	60.10	56.90	56.90
Average daily demand for M2 (units/day)	0.00	1.00	0.00	0.90	0.00	37.90	37.90
Average daily demand for M3 (units/day)	0.00	0.00	1.00	26.60	0.00	31.60	31.60
Machining time (min/unit)	69.80	85.60	107.30	129.70	0.00	12000.00	12000.00
Upholstery time (min/unit)	57.50	71.20	86.80	0.00	195.90	9600.00	9600.00
Assembly time (min/unit)	8.70	11.30	13.90	0.00	65.50	1440.00	1440.00

x1	117
x2	37
x3	5

Objective values	
P1 profit	0.00
P2 CO2 emission cost	0.00
P3 weighted underproduction	35.16
P4 overtime	261.40
P5 unused labour capacity	129.70

Appendix 2. Solver settings for the final priority level of Model 1