Preface

This Master's thesis is the final step of achieving a Master of Science at the Norwegian University of Science and Technology (NTNU). The degree specialization is Applied Economics and Optimization at the Department of Industrial Economics and Technology Management. This master thesis is written in cooperation with the innovation project "Respons" where among others, Distribution Innovation, Schibsted and Amedia are involved as industry partners and SINTEF as a research partner.

We would like to thank our supervisor Henrik Andersson from NTNU for excellent counselling, discussions and guidance throughout the work with this Master's thesis.

We would also like to thank Jon Urdal, CEO at Schibsted Trykk, and Andreas Norvik, CEO at Amedia Trykk og Distribusjon, for valuable input and discussions. Thank you to Nils Morten Vestskogen and Tom Sørlundsengen for showing us around the Amedia printing facilities at Stokke and Biri, and to Ole Hermann Melby for showing us around the Nydalen printing facilities. Additionally, we would like to thank Irene Larsen and Morten Kringler from Amedia Trykk og Distribusjon, Per Iversen from Aftenposten, Tone Løyland from Distribution Innovation and Geir Hasle from SINTEF for their cooperation and input.

Trondheim, 16.06.2014

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Abstract

One of the defining characteristics of the newspaper industry is that the products are virtually worthless at the end of the day; nobody wants to pay for yesterday's news. In addition, strict delivery deadlines and no inventory lead to very short time frames for production and distribution. Consequently production and outbound distribution are intimately linked and should be coordinated in order to achieve the objective of on-time delivery performance at minimum total cost. The increase in online publishing the last decade has led to a general drop in circulation numbers and reduction of advertising revenues. Another consequence of online publishing is that the pressure to include last minute news in the printed editions has been somewhat reduced. There are several unresolved logistical problems in the media industry, for instance the question of where to produce which products in order to optimize the distribution. In Norway it is common for media corporations to collaborate on distribution, but there is little cooperation with respect to where products should be printed.

The purpose of this thesis is to develop a model that can be used to identify cost saving potentials in the newspaper industry. We formulate a deterministic cost minimization arc-flow model that integrates facility location, production allocation, production scheduling and vehicle routing for the first echelon of the distribution. The model includes multiple facilities and products, production in time slots, changeover times between production of different products, split deliveries, a heterogeneous vehicle fleet and delivery time windows.

The arc-flow model is reformulated to a path-flow formulation using Dantzig-Wolfe decomposition (DWD). Two different decomposition strategies are developed. The first strategy decomposes into two subproblems (D2SP), one for the production and scheduling which is solved for each facility, and one for the vehicle routing which is solved for each vehicle and route. The second decomposition strategy (D1SP) includes the production allocation and scheduling in the master problem while the vehicle routing is in the subproblem.

Feasible routes are generated a priori and column generation is used to solve the linear programming (LP) relaxation of the integer programming (IP) problem. Different column generation procedures for the vehicle routing subproblem have been tested for each of the decomposed models. Procedures that add fewer columns per iteration reduce the solution time for the root node by over 50% for both of the decomposed path-flow models. The way in which vehicles and routes are ordered for solving the vehicle routing subproblems also influences the solution time.

DWD and general Branch and Bound does not guarantee optimality, or even feasible integer solutions, for IP problems. With the aim of improving the IP solution, two fixing strategies that allow for additional column generation after the root node is solved are implemented in both of the path-flow models. The fixing strategies successively fix vehicles to facilities or routes and re-apply column generation. For D2SP, fixing vehicles to routes improves the communication between the two subproblems which improves the integer solution considerably. D1SP performs better than D2SP due to a more integrated formulation and so the fixing strategies do not improve the integer solution found through Branch and Bound. A comparison of the three models reveals that the arc-flow model is better at finding feasible solutions on small instances, while D1SP is the better choice for larger instances. Both of the

decomposed models provide better LP bounds than the arc-flow model, with D2SP providing by far the best bound.

D1SP is able to find good solutions within a reasonable time frame, and is used to conduct an economic analysis on a case from the newspaper industry in South-Eastern Norway. Two of the largest printing facilities in Norway are considered: Amedia's printing facility at Stokke and Schibsted's printing facility in Nydalen, and seven of Amedia and Schibsted's largest newspaper titles. An analysis of the effect of cooperation between Amedia and Schibsted with respect to printing demonstrates that there lies a significant value in cooperating. Full cooperation with traditional offset printing results in a more centralized production and a 9% decrease in distribution costs due to a 24% reduction in the distance driven. The effect of digitalizing the printing process has also been studied. The biggest obstacle for changing to digital printers today is the print rate. However, technology for digital print is improving rapidly and with increased production rates digital print can lead to more efficient routing and considerable reductions in distribution costs. This is due to an increased flexibility in production allocation and scheduling which leads to production closer to customers. Moving the newsroom deadline forward amplifies the effects of cooperation and digitalization, decreasing the distribution costs further.

The numeric findings are case-specific and our model only considers costs, excluding other factors that are important in decision making, such as e.g. the media corporations' marketing strategies, environmental and social aspects.

It is worth mentioning that our model is not only applicable for the newspaper industry but can with certain modifications be used for problems in other industries with time-sensitive products. The model is especially useful if integration of production allocation, scheduling and distribution is important in order to minimize facility or production costs and optimize distribution.

Sammendrag

En av de definerende karakteristikkene ved avisindustrien er at produktene er praktisk talt verdiløse ved slutten av dagen; ingen ønsker å betale for gårsdagens nyheter. I tillegg fører strenge leveringsfrister og ingen lagermuligheter til svært korte tidsrammer for produksjon og distribusjon. Følgelig er produksjon og distribusjon nært knyttet og bør samordnes for å oppnå målet om punktlig levering til lavest mulig totalkostnad. Økningen i nettaviser det siste tiåret har ført til en generell nedgang i opplagstall og lavere annonseinntekter. En annen konsekvens av økningen i nettavisene er at presset for å inkludere siste nyheter i de trykte utgavene har blitt noe redusert. Det er flere uløste logistikkproblemer i mediebransjen, for eksempel spørsmålet om hvor produktene skal trykkes for å optimere distribusjonen. I Norge er det vanlig for mediebedrifter å samarbeide innenfor distribusjon, men det er lite samarbeid med hensyn til trykking av aviser.

Hensikten med denne oppgaven er å utvikle en modell som kan brukes til å identifisere potensielle kostnadsbesparelser i avisbransjen. Vi formulerer en deterministisk kostnadsminimerende arc-flow modell som integrerer valg av trykkeri, produksjonsallokering av avistitler, produksjonsplanlegging og ruting av kjøretøy for første distribusjonsledd. Modellen inkluderer flere trykkerier og produkter, produksjon i tidsluker, omstillingstider mellom produksjon av ulike produkter, mulighet for delte leveranser, heterogene kjøretøy og tidsvinduer for levering.

Arc-flow modellen er omformulert til en path-flow formulering ved bruk av Dantzig-Wolfe dekomponering (DWD). To ulike dekomponeringsstrategier utvikles. Den første strategien deler problemet i to subproblemer (D2SP), ett for produksjonsplanleggingen som er løst for hvert trykkeri, og ett for rutingen som er løst for hvert kjøretøy og hver rute. Den andre dekomponeringsstrategien (D1SP) inkluderer produksjonsallokering og planlegging i masterproblemet mens rutingen er i subproblem.

Rutene er pre-generert og kolonnegenerering blir brukt til å løse den lineære relaksjonen av heltallsproblemet. Forskjellige kolonnegenereringsprosedyrer for ruting-subproblemet blir testet for hver av de dekomponerte modellene. Prosedyrer som legger til færre enn alle kolonner per iterasjon reduserer løsningstiden i rotnoden med over 50 % for begge de dekomponerte modellene. I hvilken rekkefølge biler og ruter er ordnet når ruting-subproblemet blir løst påvirker også løsningstiden.

DWD og generell Branch og Bound garanterer ikke optimalitet for heltallsproblemer, heller ikke lovlige heltallsløsninger kan garanteres. Med sikte på å forbedre heltallsløsningene har to fikseringsstrategier som gir mulighet for ekstra kolonnegenerering etter rotnoden er løst, blitt implementert i begge path-flow modellene.

Fikseringsstrategiene fikserer biler suksessivt til trykkerier eller ruter og utfører kolonnegenerering på nytt. For D2SP modellen forbedrer fiksering av biler til ruter kommunikasjonen mellom de to subproblemene, hvilket forbedrer heltallsløsningen betraktelig. D1SP fungerer bedre enn D2SP på grunn av en mer integrert formulering, og dette fører til at fikseringsstrategiene ikke forbedrer heltallsløsningen som blir funnet ved å bruke Branch og Bound uten å generere flere kolonner etter rotnoden. En sammenligning av de tre modellene viser at arc-flow mod-

ellen er bedre til å finne lovlige løsninger på små instanser, mens D1SP er et bedre valg for større instanser. Begge de dekomponerte modellene gir bedre optimistiske nedre grenser enn path-flow modellen, men D2SP gir den klart beste grensen.

D1SP er i stand til å finne gode løsninger innenfor en rimelig tidsramme, og brukes til å gjennomføre en økonomisk analyse av et case fra avisbransjen i Sør-Øst Norge. To av de største trykkerier i Norge blir vurdert, Amedia sitt trykkerianlegg på Stokke og Schibsted sitt trykkeri i Nydalen, og syv av Amedia og Schibsted sine største avistitler. En analyse av verdien som Amedia og Schibsted kan oppnå ved å samarbeide på trykking av aviser viser at det ligger en betydelig verdi i å samarbeide. Fullt samarbeid med bruk av tradisjonell offset-trykk resulterer i en mer sentralisert produksjon og en 9 % reduksjon i distribusjonskostnader på grunn av en 24 % reduksjon i distansen kjørt. Effekten av å digitalisere trykkeprosessen har også blitt analysert. Det største hinderet for å skifte til digital trykking i dag er trykkhastigheten, men teknologien for digitaltrykk har forbedret seg mye det siste tiåret og med økt produksjonshastighet kan digital trykking føre til mer effektiv ruting og betydelige reduksjoner i distribusjonskostnader. Dette er på grunn av en økt fleksibilitet i produksjonsallokering og planlegging som fører til produksjon nærmere kunder. Å flytte redaksjonell deadline fremover forsterker effekten av samarbeid og digitalisering ved at distribusjonskostnadene blir ytterligere redusert.

De numeriske funnene er case-spesifikke og vår modell vurderer bare kostnader, og ser bort fra andre faktorer som er viktige i beslutningsprosesser, som for eksempel mediehusenes markedsføringsstrategier, miljø og sosiale forhold.

Det er verdt å nevne at vår modell ikke bare er relevant for avisbransjen, men kan med visse modifikasjoner brukes for å løse andre problemer i industrier med tidssensitive produkter. Modellen er spesielt nyttig hvis integrasjon av produksjonsallokering, planlegging og distribusjon er viktig for å minimere produksjonskostnader og optimere distribusjonen.

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Integrated production allocation, scheduling and distribution

4. Bedømmelse

Kandidatene skal ha *individuell* bedømmelse ☐
Kandidatene skal ha *felles* bedømmelse ☒

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Originalen oppbevares på instituttet.

Contents

1 Introduction

The newspaper industry has several distinctive characteristics that make it stand out from other industries. Strict delivery deadlines and little or no possibilities for keeping inventory lead to very short time-frames for production and distribution. On the one side there is a pressure from the newsroom to push the start of production as late as possible in order to include last minute news, while there is a pressure from production and distribution to start production as early as possible.

The increase in online publishing has put economic pressure on the newspaper industry. Most newspapers now offer an online product in addition to a paper copy. Circulation numbers for printed editions have dropped significantly in the last decade. As a result advertising revenues have also declined, compounded by the fact that the advertising revenues from online publishing are lower than for printed newspapers. Consequently it is crucial for the newspaper industry to cut costs or increase revenue from other business areas. Another consequence of online publishing is that the pressure to include last minute news in the printed editions has been somewhat reduced.

With the economic pressures the newspaper industry is facing today it is increasingly important to have an optimized supply chain design in order to achieve the objective of delivering the newspapers on time, at a minimum cost. Distribution costs constitute a large proportion of the total costs and consequently cost reductions in this part of the supply chain are especially effective. There are many unresolved logistical tasks in the newspaper industry. Media corporations often cooperate with respect to distribution, but there is little cooperation with respect to where products should be printed with the goal of effective total logistics. It seems to be a large cost saving potential for this industry.

The aim of this thesis is to establish a model that considers allocation of production as well as production scheduling and vehicle routing with time windows. The model should determine the allocation of editorial products to facilities, scheduling of products on several machines and split delivery to drop-off points. The goal is to use the model to determine cost saving potential.

An arc-flow formulation and reformulated as a path-flow model. With the aim of improving the LP bound and solving larger instances the arc-flow model is reformulated and decomposed using the Dantzig-Wolfe decomposition method. Two different decomposition strategies are developed, resulting in two alternative path-flow models. Several different column generation procedures are tested, and two fixing strategies are applied to both of the decomposed path models to allow for column generation after the root node has been solved. The arc-flow and two path-flow models are compared with respect to LP bound, solution time and ability to find good solutions for different problem sizes.

The path-flow model that performs best is used to solve a problem which considers two of the largest printing facilities in Norway, owned by the two largest media corporations Amedia and Schibsted, and seven of their largest newspaper titles in Eastern Norway. The model is used to perform an economic analysis to quantify the value of cooperation between the two media corporations with respect to production allocation. The effects of digitalizing the printing process and moving editorial deadlines are also evaluated.

In Chapter 2 we present an overview of the newspaper industry, the newspaper supply chain and the Norwegian newspaper industry. Chapter 3 presents a review of literature relevant to our problem. Chapters 4 presents the problem description and assumptions. The mathematical formulation of the arc-flow model is presented in 5. Chapter 6 includes theory and basic principles for Dantzig-Wolfe decomposition as well as the mathematical formulations of the two different decomposition strategies used for the path-flow model. For the path-flow models pre-generated routes are used, and the procedure for generating routes is explained in Chapter 7. Chapter 8 describes the case we study in the computational study which consist of a the technical analysis in Chapter 9 and the economic analysis in Chapter 10. Conclusions are presented in Chapter 11 before future work and extensions of the model are discussed in Chapter 12.

2 Newspaper Industry Overview

2.1 Newspaper Industry Characteristics

One of the defining characteristics of the newspaper industry is that the products are virtually worthless at the end of the day; nobody wants to pay for yesterday's news. In addition, the newspaper products are never identical from day to day, the content is changed and the size, shape and configuration may also vary. Due to the perishable nature of the product, the time from the start of production to the delivery of the finished product to the end-customer is shorter than for most other industries. [P3L, 2006]

Most daily newspapers are published in the mornings, evening papers used to be quite common but are now scarce. It is customary for newspapers to guarantee delivery of subscription papers before 6AM, and meeting this delivery deadline is of utmost importance. As a consequence of the time-pressure most production and distribution is carried out at night and often in short shifts [P3L, 2006]. Another consequence of the time-pressure and perishable product nature is that there is no inventory, i.e. newspapers cannot be made to stock.

In addition to the fact that newspaper products rarely are identical from day to day there can also be great variation between different newspaper titles with respect to format, paper quality, publication frequency, and which subscription plans that are offered. These are all contributing factors to the complexity of planning newspaper production, as no two products, weekdays or weeks are equal. Most modern newspapers come in one of three sizes; broadsheet, tabloid or midi. Traditionally broadsheet newspapers were considered to have more intellectual or serious content while tabloids (which are half the size of a broadsheet paper) were considered to be more sensationalistic. However, in more recent times many traditional broadsheet papers have converted to the more compact tabloid format in order to facilitate readability. Most newspapers are printed on inexpensive low-grade paper, usually off-white in colour. Some newspapers do however choose coloured paper, such as the Norwegian newspaper Dagens Næringsliv, which is printed on salmon pink paper. Large national and regional newspapers are often published daily while smaller and local titles are often published weekly or bi-weekly. Saturday and Sunday editions of daily newspapers are commonly larger than the weekday editions. Many newspapers also offer a variety of subscription plans, e.g. daily, only weekdays or only weekends.

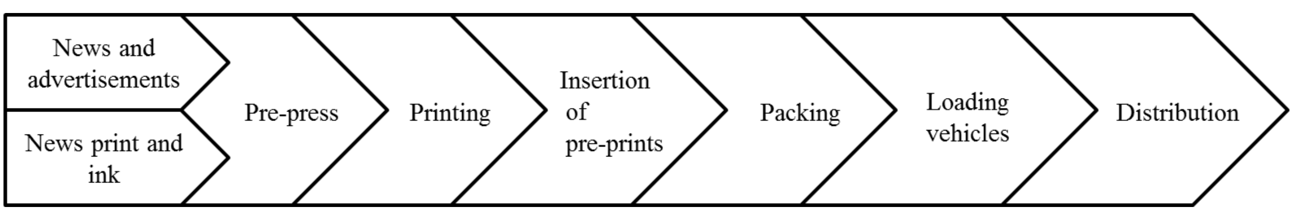
The primary costs in the newspaper supply chain are related to production of editorial content, capital and operational expenses of running printing facilities (including material, labour, utilities costs etc.), in addition to labour, vehicle and fuel costs at the distribution level. The cost structure varies widely from country to country, but on average printing and distribution costs account for 2/3 of the costs associated with running a newspaper [Hasle, 2012]. Cost reductions in these parts of the supply chain are therefore especially effective, and should be a primary focus area for all newspaper producers. If subscription newspapers are delivered late, subscriptions may be cancelled, but if they are delivered on time profits will not increase, thus the general objective of the newspaper industry is to provide the required service level at minimum cost [Van Buer et al., 1999].

A newspaper's revenues basically consist of subscription revenue, counter sales and advertising revenue. Traditionally newspapers have derived more than 50% of revenues from advertising, with the exception of newspapers that are subsidized by governments and therefore rely less on advertising revenue. [Picard and Brody, 1997] The last decades have seen a rapid growth in online publishing, as well as the emergence of news broadcasting via 24-hour television channels, which has led to a decline in circulation and advertising revenues for newspapers in developed countries. Paid readership of print newspapers has, however, been on the rise in the main developing nations [OECD, 2010]. Online advertising is often less effective and prices are lower, which in combination with the global economic recession in the late 2000s –early 2010s and declining circulation numbers for printed editions has led to steadily declining profits in the newspaper industry in the western world. With the economic pressure the newspaper industry is under it is increasingly important to have an optimized supply chain design and a high degree of operational coordination in order to achieve this objective. Additional measures that could contribute to minimizing costs are outsourcing and consolidation of logistics between companies at the strategic level. [Hasle, 2012]

2.2 Newspaper Supply Chain

The supply chain for printed newspapers largely consists of production of editorial content, manufacturing, and distribution. Manufacturing includes the pre-press production, printing and packing. The distribution includes both first-stage delivery to distribution centers or drop-off points as well as final delivery to retailers and subscribers.

Figure 1: *The newspaper supply chain*



2.2.1 Editorial content

The editorial content is created by a combination of journalists, reporters, photographers, editors and news agencies. “Hard” news stories are often supplied to the newspapers by news agencies such as the Associated Press or Reuters, and may be reported directly or used as background information for feature pieces. After editing and graphical work fully digital versions are sent to the printing facilities via internet before the deadline for production start. Finished newspaper pages are often sent to the printing facilities continuously as soon as they are finished. This means that the printing facilities can start the pre-print process for finished pages well ahead of the newsroom deadline.

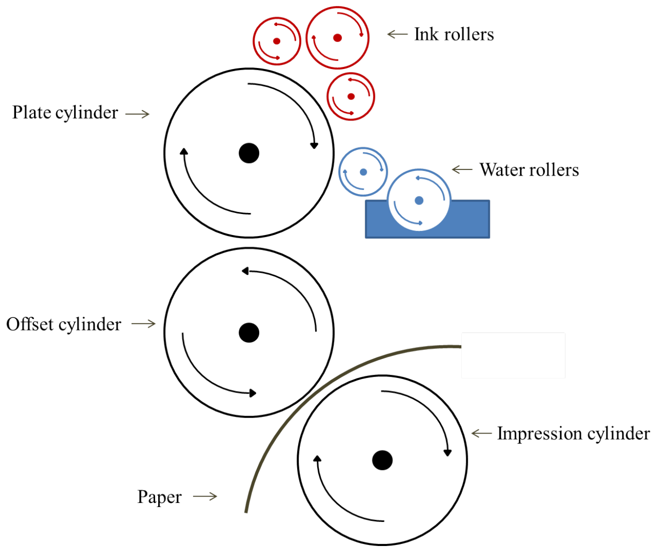
2.2.2 Manufacturing

The manufacturing of newspapers can be divided into three production stages; pre-print, printing and packaging. The most commonly used printing process for daily newspapers is offset printing which uses printing plates.

Pre-print production

The pre-print stage is an important part of the manufacturing and often takes place in the same facilities as the printing. In this stage the printing facilities receive pages from the newsroom in a digital format (e.g. pdf) that are processed in preparation for printing and physical printing plates are produced [Schibsted, 2014]. In modern print works the pre-print process is digitalized through so-called computer-to-plate technology. Only four colours of ink are used in the printing process and a separate printing plate is made for each of these colours. (Black-and-white pages only need one plate.) During pre-print the pages are digitally converted to the CMYK colour model which results in one file for each of the primary colours, cyan (blue), magenta (red), yellow and key (black) [Mine, 2001]. For media corporations that print the same editions at several printing facilities this job is often centralized. Once the files are finalized four printing plates are produced for each double page (see Figure 2). The plates used in offset printing are thin, flexible, and usually made of aluminum. The plates cannot be re-used for newspaper printing but can be recycled or sold at close to new aluminum prices.

Figure 2: *One of the four printing plates made for a double page*



(a) Side view of the offset printing process [Kipphan, 2001]

(b) Printing plates fastened to a print tower

Figure 3: *Offset printing process*

Printing process

Offset printing is the most commonly used technique in newspaper production. Offset printing builds on the lithographic process, which is based on the principle that oil and water repel each other. Images are etched onto aluminum plates treated with a greasy emulsion. The parts of the image that are to be printed are covered with the emulsion and will attract ink while repelling water, whereas the ink will be washed away from the print-free areas [Kipphan, 2001]. The printing plates are mounted on plate cylinders (see Figure 3) in printing towers and inked with a combination of water and ink [Newspapers in Education, 2009]. The ink from the printing plates is transferred to a rubber blanket cylinder and then offset to paper [Encyclopædia Britannica, 2014]. Large paper rolls are fed through the printing towers which print continuously as one long stream of paper passes by.

In order to change from printing one edition to another, printing plates must be changed. The changeover time will vary depending on whether only a few pages or an entire edition is changed. When changing between products printed on different paper types the changeover time will also be longer.After printing the paper goes through stitching machines where the paper streams are put together in the right order, cut, assembled and stapled together. Figure 4 shows a paper stream going into a stitching machine.

Web presses can print at very high speeds with up to 80,000 impressions per printing tower per hour. Depending on the size of the newspaper page and type of machinery one impression prints between 8 and 32 pages. The capacity of the printing process is limited by the number of press towers and stitching machines and the speed of these. The number of press towers determines the number of pages which can be printed at the same time and the number of stitching machines determines how many editions can be produced at the same time.

Figure 4: *Paper going into a stitching machine*

Other media products, such as magazines and advertising material, are printed on digital printers. Digital printing requires no tool change and thus changeover time between editions is negligible. Digital printers have a significantly lower production rate than modern printing presses. Offset presses can print up to 8 times faster than digital printers [Kringler and Larsen, 2013]. Due to the strict time constraints in the newspaper industry it is not common practice to use digital printing. However, as the digital printing technology is developed the production rates are improving and it is likely that newspaper printing will become increasingly digitalized in the future [Kringler and Larsen, 2013]. The elimination of changeover times and production of printing plates justifies production of the same edition in several locations, which could lead to a reduction in distribution costs.

Packaging

After assembling and stapling, the newspapers are usually transported to the packaging area clipped to a gripper-conveyor in the ceiling (see Figure 5). In the packing area inserts such as advertisements and pamphlets are often added by insertion machines. The newspapers are then packaged in bundles according to delivery locations with drop-off information on packing slips. The packages are allocated to loading ramps where they are loaded onto vehicles for distribution. Packaging and vehicle loading are potential bottlenecks in the supply chain and seeing as inventory space usually is limited, the printing, packaging and vehicle dispatching have to be closely coordinated [Hasle, 2012].

Figure 5: *Gripper-conveyor system at Nydalen printing facilities*

Figure 6: *Loading ramps at Nydalen printing facilities*

2.2.3 Distribution

Transportation from the printing facilities to the end-customer is often carried out in several stages, in a multi-echelon distribution chain. Counter sale newspapers are either delivered to distribution centres for further distribution or delivered directly to retailers. In the counter sales supply chain reverse logistics are also included. Retailers often only pay for the copies that are sold and return of unsold copies may be required for verification reasons. The daily production of an edition is based on sales numbers for each specific day from all the retailers.

For subscription newspapers the first echelon transport ends at either distribution centres or drop-off points where newspaper carriers collect their newspapers. Drop-off points typically do not require direct capital investment but can be located at e.g. a street corner, gas station or public area. Several carriers may pick up their newspaper packages at the same drop-off point [Van Buer et al., 1999]. The packages may contain different newspaper titles in addition to other media products such as magazines, books or direct marketing material [Hasle, 2012]. For morning papers the deliveries to drop-off points typically take place between 12 AM and 4 AM. In the final stage of the subscription supply chain the newspaper carriers deliver the newspapers to the subscribers' postbox or doorstep. The first echelon is often carried out in larger vehicles while final stage delivery utilizes smaller vehicles or alternatively the carriers deliver the subscription papers by bicycle or on foot. It is common for several newspapers to coordinate the distribution of their products, either through cooperation or through outsourcing distribution to third party distribution companies.

2.3 The Norwegian Newspaper Industry

The first Norwegian newspaper was published in 1763 and today there are more than 200 newspaper titles with at least one weekly edition [Store norske leksikon, 2014]. There are three major media groups in the Norwegian newspaper industry; Schibsted, Amedia and Polaris Media. These media corporations each own many newspaper titles. Table 1 presents the number of newspaper titles each of the media corporations own, in addition to total daily circulation numbers and market share.

Table 1: *Norwegian newspaper market*

	Newspapers	Daily circulation	Market share [%]
Schibsted	15	738 000	31
Amedia	66	615 000	25
Polaris Media	26	221 000	9

[Medienorge, 2013]

Schibsted is the largest media corporation in Norway and owns large national newspapers such as Aftenposten and VG. Amedia is the largest local newspaper owner with titles such as Drammens Tidende and Bergensavisen. Polaris Media is the largest north of Trondheim and its most sold newspaper is Adresseavisen.

With regards to e.g. distribution of newspapers the media groups cooperate to a certain extent. Especially in the Eastern part of Norway the cooperation between Schibsted and Amedia is high when it comes to distribution, i.e. they use the same distribution companies and coordinate the delivery of their newspapers in different regions. Schibsted distributes a lot of Amedia's newspapers in the greater Oslo area and vice versa outside the capitol [Kringler and Larsen, 2013]. Together, Amedia and Schibsted own Distribution Innovation LC, which provides software and solutions for distribution optimization for almost all the Norwegian newspapers [Distribution Innovation, 2014]. Another area of cooperation is within distribution of products such as magazines, books and advertising material, which is delivered together with the newspapers. Mediapost LC coordinates this and is also owned by Schibsted and Amedia [Mediapost, 2014]. Even though there is a high level of cooperation within distribution there is still little cooperation regarding the printing of newspapers. Amedia and Polaris Media cooperate to a certain extent in some cases, e.g. they co-own a printing facility in Orkanger south of Trondheim, and Polaris Media prints some Schibsted-owned newspapers in Trondheim and Harstad [Polaris Media, 2014]. Apart from this there is hardly any cooperation with respect to printing, and especially in the Eastern part of Norway there is strong competition between Schibsted and Amedia. Figure 7 shows the five printing facilities covering this region. Four of them are owned by Amedia (a) and one by Schibsted (s). There is excess capacity in the printing facilities in this region.

Figure 7: *The five major printing facilities in Eastern Norway*

An important motivational factor for increased collaboration with respect to distribution is the possibility for increased revenues [MediaPost and Innovation, 2004]. A large national distribution network enables distribution of other products than newspapers. The motivation for cooperating on printing, on the other hand, is not as strong. Collaboration could potentially lead to cost reductions, but would at the same time decrease market positioning with respect to having available capacity to print new products. Even though cooperation exists in certain business areas, all of the three major media corporations are competitors. However, many printing facilities have been closed down in the last ten years and increased cooperation within printing may be necessary in the future in order to cut costs.

3 Literature Review

Our problem includes several different decisions, including the possibility of deciding which printing facilities to use, the allocation of editorial products to facilities, scheduling of products and the vehicle routing to drop-off points with time-windows. The objective is to minimize costs. The formal description of our model is a Production Allocation Problem with Production Scheduling and Vehicle Routing with Time Windows, although to simplify we refer to it as a Production Allocation and Scheduling Problem with Routing (PASPR).

We have chosen to divide the literature review into subsections for each of the basic problem types that are integrated in our problem. These include routing, facility location or production allocation and production scheduling problems. We also present literature related to integrated problems that include combinations of the basic problems. After reviewing the integrated problems we present an overview of publications specifically related to the newspaper industry.

3.1 Basic problems

3.1.1 Routing

Extensive research has been done on the subject of vehicle routing. Christiansen [1996] gives a comprehensive description of the different variations of routing problems, the research done on them and associated solution approaches. The author starts with a description of the general Shortest Path Problem (SSP), and moves on to the Travelling Salesman Problem (TSP) before looking at the Vehicle Routing Problem (VRP). Then time window constraints are added to all the mentioned variations, and more complex modelling and solution approaches are presented. Within VRP with Time Windows (VRPTW) a distinction can be made between soft and hard time windows [Ullrich, 2013]. Hard time windows cannot be violated while soft time windows allow violation but add a penalty for delays. The penalty for delay can reflect for example reputational damage or contractual penalties. In many real world cases upper time window constraints must be seen as soft in order to achieve feasible solutions. Solving the VRPTW is NP-hard [Boonkleaw et al., 2009] and therefore heuristic solution methods are usually applied. Optimal solution approaches have not been given the same focus as heuristics in the literature, but Christiansen [1996] proposes three different methods; state-space relaxation, Lagrangean relaxation and Dantzig-Wolfe decomposition. Baldacci et al. [2012] report that the best exact solution methods for the VRPTW published the last few years are based on a Set Partitioning formulation. Here each feasible route has a binary variable and each customer must be covered by one route. Baldacci et al. [2012] also mention the importance of adding valid inequalities to strengthen the formulation. Even though there has been an increased focus on exact solution approaches recently, the application of these approaches is limited for many routing problems [Schmid et al., 2013]. Schmid et al. [2013] highlight Tabu Search (TS) and Variable Neighborhood Search (VNS) as common heuristics to solve the VPRTW. TS searches in the neighborhood of the current solution for allowed solutions, but avoids attributes which are declared tabu for some iterations. VNS explores the current neighborhood by only accepting improving moves. If no more improving moves are possible the algorithm moves onto the next neighborhood. Schmid et al. [2013] also points out the recent interest in matheuristics which combine heuristics with exact approaches. Three main approaches are identified as most common; set covering formulations with feasible routes, local branching and decomposition into subproblems based on exploitation of problem structures.

3.1.2 Facility location

Facility location decisions are an important part of the strategic design of supply chain networks [Melo et al., 2009]. General facility location problems (FLP) include a set of spatially dispersed customers and a set of facilities that can serve customers. Facility location problems aim to determine which facilities should be used, and/or which customers should be serviced from which facility in order to minimize the total costs, while taking distances, times or costs between customers into consideration. [Melo et al., 2009]

Daskin [1995] , ReVelle and Eiselt [2005] and Klose and Drexl [2005] all provide detailed and systematic introductions to the field of facility location problems. Klose and Drexl [2005] review different facility location models for distribution systems. They consider many different approaches ranging from simple models to more complicated ones. They start differentiating between continuous and discrete location models. In the former, facilities can be located at any point in the plane using a coordinate system. In the latter, the selection of the locations for the facilities is restricted to a defined set of available candidate locations. Our model includes a discrete facility location problem. These problems can be modelled as mixed-integer problems, and the authors present several model propositions. The least complicated is an uncapacitated, single-stage, single-product, static model without routing. The review explains how their model expands as the problem complexity increases. Model extensions include capacitated facilities, multi-stage locations, multi-product production, dynamic decisions with several periods and routing.

3.1.3 Production scheduling

Scheduling is one of the most widely researched areas of operational research. Potts and Strusevich [2009] present a comprehensive survey that explores the historical development of scheduling since the mid-1950s. Main topics of scheduling research from the past five decades are discussed, and the key contributions that helped shape the subject are highlighted.

Our problem includes production scheduling with setup or changeover times and costs. Allaverdi et al. [2008] survey over 300 papers on scheduling with setup times or setup costs. The survey divides the literature into; 1. Shop environments, which include single machine, parallel machines, flow shops, job shops and open shops, 2. Batch and non-batch setup times, 3. Sequence-dependent and sequence-independent setup costs and 4. Job and batch availability models. Our problem is one of parallel machines and sequence-dependent setup times, although we simplify to using sequence-independent setup times. The majority of the papers address sequence-independent setup times because sequence dependent setup times are more difficult to deal with. The most common solution methods for scheduling problems with setup costs include branch-and-bound, mathematical programming formulations, dynamic programming algorithms, heuristics and meta-heuristics.

Since our problem integrates production scheduling and distribution we focus on presenting publications that deal with integrated problems. These will be presented in section 3.2.2. For a review of traditional scheduling publications we refer to Potts and Strusevich [2009] and Allaverdi et al. [2008].

3.2 Integrated problems

3.2.1 Location-routing problems

In their review of facility location and supply chain management literature Melo et al. [2009] identify basic features that location models must capture to support decision-making involved in strategic supply chain planning. In particular, the integration of location decisions with other decisions relevant to the design of a supply chain network is discussed. An example is integration of location and routing problems (LRP). Both FLP and routing problems are actually special cases of the LRP. When all customers are directly linked to a depot the LRP is a standard facility location problem, and when the depot locations are fixed the LRP reduces to a VRP Nagy et al. [2007].

According to Klose and Drexl [2005] location problems with routing are extremely complicated. The most important reason being the large variety of location model alternatives combined with the vast number of routing models. Other reasons are different planning horizons for location and routing decisions and the fact that location problems, in contrast to routing problems, require demand aggregation.

Nagy et al. [2007] present a survey of location routing problems. The authors classify them according to eight aspects of the problem structure:

1. The hierarchical structure of the problem. The most common is for facilities to be connected to customers and not to other facilities.

2. The type of input data, which can be either deterministic or stochastic.

3. The planning period, which can be either static or dynamic.

4. The solution methods, which can be exact or heuristic.

5. Objective function, where the most common is cost minimization.

5. Solution space, which can be either discrete or continuous.

6. The number of depots, which can be single or multiple.

7. The number and type of vehicles. The problems most commonly consider a homogeneous fleet and do not fix the number of vehicles in advance.

8. Route structure. In most problems the vehicles start at the facility, traverse customers and return.

Our problem has deterministic input data, discrete solution space, multiple depots and a cost minimizing objective function. The hierarchical and route structure consists of facilities servicing customers in tours and vehicles returning to the original facilities. There are no connections between the facilities.

Nagy et al. [2007] point out that very few authors have investigated integrating location-routing with other aspects of distribution management, such as e.g. production scheduling. However, recently an increasing amount of research has focused on the area of integrating production scheduling and routing. Literature on this subject is discussed in the following section.

3.2.2 Integrated production scheduling and distribution problems

As mentioned earlier perishable goods, such as newspapers, are time-sensitive products that need to be delivered to customers immediately after production and consequently have little or no inventory. This leads to a very close link between production and outbound distribution. Therefore, to achieve a high level of service (i.e. on-time delivery performance) at minimum cost, it is necessary to schedule production and distribution together as an integrated problem. According to Chen [2010] research on integrated production scheduling and distribution (IPSD) is relatively new, but is growing rapidly.

Sarmiento and Nagi [1999] review work in the area of integrated analysis of production-distribution systems. The survey shows that the integration of logistics and production functions has the potential of providing significant benefits in the form of cost savings and efficiency improvement.

Chen [2004] and Chen [2010] also carry out an extensive review of literature that includes existing models and publications on this subject. The literature is divided into studies focusing on simple delivery operations, i.e. direct to destination, and vehicle routing. The studies on simple delivery operations are divided into studies including single job destinations (e.g. a single distribution center) and multiple job destinations (e.g. several customers). The vehicle routing problems are divided into studies with deliveries with and without delivery deadlines. Our problem is one of integrating scheduling of machines and vehicle routing with time windows and we will therefore focus on literature related to these types of problems.

Chen and Vairaktarakis [2005] consider a problem with one facility, multiple destinations and an infinite fleet of capacitated vehicles. They address scheduling problems with both single and multiple parallel machines. The objective is to minimize average arrival time and distribution costs, which are composed of the costs of the number of vehicles used and routing costs. The problem is solved through tailor-made algorithms and the authors compare their integrated approach with decomposition approaches, concluding that integration leads to improved performance of between 12 and 40%.

Garcia et al. [2004] consider a problem that includes several facilities with parallel machines, and vehicles that can only deliver one job at a time. The jobs can only be produced at certain job-specific facilities and must be delivered to the customer site immediately after production is completed, within a deadline. The authors present an integer programming model that maximizes the weighted value of the orders served. A special case of the problem is considered, which can be solved in polynomial time by a minimum cost flow algorithm. Based on this approach a heuristic procedure for the general case is developed.

According to Chen [2010] VRPTW's have been studied extensively, but there has been little focus on integration of production and outbound distribution scheduling with both routing and time windows (IPDSPVRTW). Chen points out that these problems are more difficult than any other class of IPSD problem, but that because of their practicality more research should be conducted in this area.

Ullrich [2013] proposes a solution to an IPDSPVRTW. The author proposes two subproblems, one for machine scheduling and one for vehicle routing which are linked and integrated by the completion times of the jobs. In contrast to our approach, which minimizes cost, the aim of Ullrich's problem is to minimize total tardiness. The problem is NP-hard and is solved by a genetic algorithm and two decomposition approaches. Ullrich demonstrates that the integrated solution method yields far better results than when decomposing into subproblems and aggregating the solutions from these. Ullrich concludes that through integration of machine scheduling and vehicle routing it is possible to improve overall performance and that future research in this area "clearly demands more research" and would be highly worthwhile. Especially companies selling time-sensitive goods should consider integrating production and distribution planning [Ullrich, 2013].

3.3 Newspaper production applications

This section reviews literature specific to the newspaper industry. Golden et al. [2002] present a survey of papers concerning the newspaper delivery problem up to 1996 which includes nine papers all focusing on first echelon distribution. Hasle [2012] presents a survey of literature from 1996 to 2011 that includes less than ten papers, indicating that the literature regarding newspaper distribution is relatively scarce. These papers also focus on the first echelon of the distribution. We focus on the publications of the newspaper delivery problem that are most relevant to our problem.

Van Buer et al. [1999] formulate a problem linking the production and distribution of several newspaper editions destined for different geographical areas. The problem includes strict delivery deadlines and the potential for setup times between editorial products. To link the production sequencing problem with the VRP the model returns a permutation vector that gives the order in which (pre-generated) routes are serviced, which in turn determines the sequence of production. The model is solved by heuristic solution methods and the authors demonstrate that there is a large cost saving potential in re-using vehicles, i.e. letting vehicles do several trips.

Song et al. [2002] consider first echelon distribution to newspaper agents. The problem integrates determining printing sequencing of editions, allocation of agents to facilities and routing from the facilities to the allocated agents. The vehicle fleet is heterogeneous and a maximum of two split deliveries are allowed, i.e. maximum two vehicles can visit the same agent. The problem is solved in two stages. In the first stage a generalized assignment problem allocates the agents to facilities and then production sequencing is determined by heuristics. In the second stage the routing is solved heuristically by taking production time and deadlines into account. The approach was tested for a Korean newspaper and found a reduction of delivery cost of 15% and reduction in delay time of 40%.

Cunha and Mutarelli [2007] consider a similar problem to Song et al. They develop a spreadsheet-based optimization model in order to determine the number and location of printing facilities to be used for a weekly Brazilian magazine. The production sequence and first echelon distribution is also considered and total cost savings of 7% are reported.

Russell et al. [2008] consider coordination of production and distribution for multi-product newspapers to drop-off points. The authors present a deterministic formulation of the open vehicle routing problem with time window and zoning constraints. Open in this case implies that vehicles do not need to return to a facility. Initial solutions are generated by a generalized network assignment problem and a tabu search metaheuristic is used to improve solutions satisfying zone constraints and probabilities of satisfying delivery deadlines. Computational results from a case study of a mid-size newspaper in Oklahoma show significant improvement in comparison to the current practice.

4 Problem Description

The main objective of the PASPR model is to determine where to produce which newspaper products in order to minimize start-up costs and first echelon distribution costs. This includes deciding the allocation of production, production scheduling or sequencing, as well as vehicle routing from the facilities to drop-off points or customers.

Simchi-Levi et al. [2009] divides decision levels into three categories; the strategic level which deals with long-term effects greater than one year, the tactical level where decisions are evaluated from a monthly to a yearly basis and the operational level which considers daily decision-making. This model includes both operational, tactical and strategic aspects. The decision of where to print which newspaper titles is usually a tactical decision, while decisions regarding scheduling and routing can be both tactical and operational. Production and routing schedules are usually planned for the medium term (often for months at a time), but new schedules can also be determined weekly or even daily for some newspapers. In addition to being a tactical and operational tool, the model can also be utilized for strategic decision-making by evaluating how different scenarios affect the total costs and decide which products to produce or which facilities to keep open.

Production and loading

The problem considers multiple printing facilities and editorial products. The location of the facilities are given and each facility may have several parallel printing presses, so different products can be printed simultaneously at the same facility. The entire demand of a product does not have to be produced at the same time, but can be printed in several batches. When changing from producing one editorial product to another the printing plates on that press must be changed, and there will be a period of time with no production on the printing press in question. For every different location in which a product is printed the printing plates for that edition must be produced, which incurs an associated cost. The production rates depend on the properties of the printing presses and what product is being printed. Some editions take longer to print due to different edition sizes and layout. All products can be printed on all presses. The production facilities are capacitated, i.e. they have a certain number of presses and production time frame. Production can only start after the newsroom deadline. The production scheduling is decided in order to optimize the distribution, in this way the products that have to be transported the longest distance can be produced first.

Routing

Newspapers are transported from the production facilities to distribution centers, also known as drop-off points, in capacitated vehicles. From the drop-off points the subscription newspapers are distributed to end-customers in smaller vehicles. The PASPR considers only the first echelon of the newspaper distribution, i.e. the final delivery stage is not included in the model. Different newspaper products can be transported in the same vehicle and a customer may have demand for several products. Every product must be delivered within a specified time window. The vehicles cannot arrive after the delivery deadline, but if they arrive before the earliest time of arrival they can wait at the customer location. This means that the problem has hard time windows, thus a penalty for arriving too late is not needed in the objective function. One vehicle may serve several customers, but can only load newspapers at one facility. Each vehicle must return to the facility it originated from. A customer can be visited by several vehicles (split delivery), but all of the demand for a given product at a given customer location must be delivered by the same vehicle, i.e. two vehicles can not deliver the same product to the same customer.

Costs and demand

The model includes printing plate costs, facility costs and costs of distributing the newspapers. The distribution costs are divided into transportation costs and the cost of using vehicles. All of the demand is deterministic and the problem considers a single time period.

4.1 Assumptions

In this section we describe the assumptions we have made when formulating the mathematical models.

Production and loading

We assume that all products can be loaded at least as fast as they can be produced. In reality this depends on how fast products can be packed and the number of loading ramps, both of which are potential bottlenecks in the supply chain. However, this can to a certain extent be accounted for by adjusting the production rate accordingly. The changeover time between products is given for each facility and press, but not for each product. In reality, changeover times are product dependent, but it is difficult to estimate the exact changeover time between two products since similar products have short changeover times, but highly different products require longer changeover times. Therefore we use the average changeover times at each facility. We discretize the time variable into time slots to make the model solvable for larger problems than a continuous time representation would have allowed for. Using time slots means that it is only possible to print in a full time slot or not at all. Since demand does not perfectly match the production rates and time slot size there will be some excessive production. In our model these items will just "disappear". In a real situation this excess production could act as a small inventory buffer, or the change of printing plates could start as soon as the exact demand of each product is completed. We assume newsroom deadlines, i.e. earliest start of production, to be product-specific. The pre-print process including production of printing plates are assumed to not delay the production of newspapers, and are therefore not considered in the model.

Routing

Drop-off points are represented by nodes in a network. The demand in each node is aggregated from a large area that surrounds the drop-off point it represents. We assume the time windows for delivery are specific for each customer, but equal for all products in one customer. The vehicle fleet is heterogeneous, i.e. different vehicles can have different costs and capacities depending on the vehicle type and size. Reuse of the same vehicle is not allowed which means a vehicle can only leave a facility once. Vehicles leave at the end of a time slot.

Costs and demand

There are no revenues directly attributed to the production-distribution function of a newspaper so we minimize costs as opposed to maximizing profits. The facility costs are assumed to be specific for each printing facility, and printing plate costs to be equal and independent of facility, press or product. In real life there is a small variation in plate cost per product, but it is not considered to be substantial. We have not included production costs (e.g. labor, raw materials and utilities) in the model because we assume these to be similar for different printing facilities, and will therefore not affect the production. The cost of using vehicles includes both cost of driver and cost of owning or hiring the vehicle. For a newspaper company the distribution costs are often combined into one cost for each route because routes are tendered to logistics companies. Distribution costs, both for using a vehicle and transportation costs, can vary with which vehicle is being used.

Since the problem considers a single time period, we assume demand to be constant. We consider this time period to be one day.

5 Arc-flow Model Formulation

In this section we present the mathematical model for the arc-flow formulation of the PASPR. The problem is formulated as a deterministic cost minimization problem. We start by defining sets, indices, parameters and decision variables, before presenting the objective function and constraints.

5.1 Definitions

We use capital letters for parameters and sets, and lower-case letters to represent decision variables and indices.

Sets and indices

I	Set of nodes i
I^C	Subset of customer nodes i
I^F	Subset of production facility nodes i
K	Set of vehicles k
M	Set of printing presses $m = 1, \dots, N^M$
P	Set of products p
T	Set of time slots $t = 1, \dots, N^T$

Parameters

A_i	Earliest possible start of service at node i
B_i	Delivery deadline at node i
C_i^F	Cost of a production facility i being open
C_{ijk}^D	The distribution cost of driving vehicle k from node i to node j
C_k^V	Cost of using vehicle k
C^P	Cost associated with producing printing plates
D_{ip}	Demand of product p at node i
M^{D1}	Maximum difference between delivery deadline and earliest possible arrival time
M^{D2}	Maximum difference between delivery deadline and earliest production start
Q_k	Capacity of vehicle k
R_{imp}	Production rate at facility i on press m for product p
S_{im}	The number of time slots required for a product change on press m in facilty i
T_{ijk}	The time it takes to drive vehicle k from node i to node j
U_t	End time for time slot t

Decision Variables

g_{impt}	Binary variable 1 if product p is produced on press m in at facility i in time slot t
h_{ip}	Number of printing plate sets needed to print product p at facility i
q_{ipkt}	The quantity of product p loaded onto vehicle k at production facility i in time slot t
w_{ijk}	Binary variable 1 if vehicle k drives from i to j
s_k	Start time vehicle k
t_{ik}	Time when vehicle k starts service at node i
x_{kt}	Binary variable 1 if vehicle k leaves at end of time slot t
y^N_{ik}	Binary variable 1 if node i is visited by vehicle k
y^C_{ipk}	Binary variable 1 if product p is delivered to customer i by vehicle k

5.2 Mathematical model

Objective function

$$min\ z = \sum_{i \in I^F} C^F_i f_i + \sum_{i \in I}\sum_{p \in P} C^P h_{ip} + \sum_{k \in K}\sum_{t \in T} C^V_k x_{kt} + \sum_{i \in I}\sum_{j \in I}\sum_{k \in K} C^D_{ijk} w_{ijk} \tag{5.1}$$

Constraints

$$N^M f_i - \sum_{m \in M}\sum_{p \in P} g_{impt} \geq 0 \qquad i \in I^F, t \in T \tag{5.2}$$

$$h_{ip} - \sum_{m \in M} g_{impt} \geq 0 \qquad i \in I^F, p \in P, t \in T \tag{5.3}$$

$$\sum_{p \in P} g_{impt} \leq 1 \qquad i \in I^F, m \in M, t \in T \tag{5.4}$$

$$S_{im}(1 - g_{imp(t-1)}) - \sum_{\rho \in P \setminus p}\sum_{\tau = t}^{t+S_{im}-1} g_{im\rho\tau} \geq 0 \qquad i \in I^F, m \in M, p \in P, t = 2, \ldots, N^T \tag{5.5}$$

$$\sum_{m \in M} R_{imp} g_{impt} - \sum_{k \in K} q_{ipkt} \geq 0 \qquad i \in I^F, p \in P, t \in T \tag{5.6}$$

$$\sum_{k \in K} y^N_{ik} \geq 1 \qquad i \in I^C \tag{5.7}$$

$$\sum_{k \in K} y^C_{ipk} = 1 \qquad i \in I^C, p \in P | D_{ip} > 0 \tag{5.8}$$

$$y^N_{ik} - y^C_{ipk} \geq 0 \qquad i \in I^C, p \in P, k \in K \tag{5.9}$$

$$\sum_{i \in I^F} y^N_{ik} \leq 1 \qquad k \in K \tag{5.10}$$

$$\sum_{i\in I^F}\sum_{t\in T} q_{ipkt} - \sum_{i\in I^C} D_{ip}y^C_{ipk} \geq 0 \qquad p \in P, k \in K \qquad (5.11)$$

$$\sum_{i\in I^F} Q_k y^N_{ik} - \sum_{i\in I^C}\sum_{p\in P} D_{ip}y^C_{ipk} \geq 0 \qquad k \in K \qquad (5.12)$$

$$Q_k y^N_{ik} - \sum_{t\in T}\sum_{p\in P} q_{ipkt} \geq 0 \qquad i \in I^F, k \in K \qquad (5.13)$$

$$\sum_{t\in T} x_{kt} - y^C_{ipk} \geq 0 \qquad i \in I^C, p \in P, k \in K \qquad (5.14)$$

$$\sum_{t\in T} x_{kt} \leq 1 \qquad k \in K \qquad (5.15)$$

$$Q_k(1 - x_{kt}) - \sum_{i\in I^F}\sum_{\tau=t+1}^{T}\sum_{p\in P} q_{ikp\tau} \geq 0 \qquad k \in K, t \in T \qquad (5.16)$$

$$\sum_{i\in I^F}\sum_{j\in I^C} w_{ijk} - \sum_{t\in T} x_{kt} = 0 \qquad k \in K \qquad (5.17)$$

$$\sum_{i\in I\setminus j} w_{ijk} - y^N_{jk} = 0 \qquad j \in I, k \in K \qquad (5.18)$$

$$\sum_{i\in I} w_{ijk} - \sum_{i\in I} w_{jik} = 0 \qquad j \in I, k \in K \qquad (5.19)$$

$$t_{jk} - \sum_{t\in T} U_t x_{kt} - T_{ijk}w_{ijk} + M^{D1}(1 - w_{ijk}) \geq 0 \qquad i \in I^F, j \in I^C, k \in K \qquad (5.20)$$

$$t_{jk} - t_{ik} - T_{ijk}w_{ijk} + M^{D2}(1 - w_{ijk}) \geq 0 \qquad i \in I^C, j \in I^C, k \in K \qquad (5.21)$$

$$A_i \geq t_{ik} \geq B_i \qquad i \in I^C, k \in K \qquad (5.22)$$

$$f_i \in \{0,1\} \qquad i \in I^F \qquad (5.23)$$

$$g_{impt} \in \{0,1\} \qquad i \in I, m \in M, t \in T, p \in P \qquad (5.24)$$

$$w_{ijk} \in \{0,1\} \qquad i \in I, j \in J, k \in K \qquad (5.25)$$

$$x_{kt} \in \{0,1\} \qquad k \in K, t \in T \qquad (5.26)$$

$$y^N_{ik} \in \{0,1\} \qquad i \in I, k \in K \qquad (5.27)$$

$$y^C_{ipk} \in \{0,1\} \qquad i \in I, k \in K \qquad (5.28)$$

$$q_{ipkt} \geq 0 \qquad i \in I, k \in K, t \in T, p \in P \qquad (5.29)$$

$$h_{ip} \geq 0 \; and \; integer \qquad i \in I, p \in P \qquad (5.30)$$

$$s_k \geq 0 \; and \; integer \qquad k \in K \qquad (5.31)$$

$$t_{ik} \geq 0 \; and \; integer \qquad i \in I, k \in K \qquad (5.32)$$

The first term of the objective function (5.1) minimizes the facility costs, the second the costs of producing printing plates, the third the cost of acquiring a vehicle and driver, and the last term describes the variable distribution costs.

Constraints (5.2) assure that if anything is produced in a given time slot at a given facility this facility must be open. Constraints (5.3) ensure that if a product is printed in a facility there is a cost for producing printing plates for that product. Constraints (5.4) prevent more than one product from being produced on a given press in the same time slot. The changeover constraints (5.5) make sure that when changing from production of one product to another the following S_{im} time slots on that press will have no production due to changing of printing plates. Before products can be loaded to vehicles they have to be produced, this is ensured by (5.6).

Constraints (5.7) ensure that all customer nodes are visited by at least one vehicle, while constraints (5.8) make sure that all the products that have demand in a node are delivered. Constraints (5.9) connect the visiting variables and the product delivery variables. If the demand for a product is delivered by vehicle k in node i then this vehicle must visit this node. Conversely, if vehicle k does not visit node i then this vehicle cannot deliver any of the products in that node. Constraints (5.10) prevent vehicles from visiting more than one facility. Constraints (5.11) make sure vehicles are loaded with all the demand in their route, while (5.12) ensure that the total demand of the customers that a vehicle visits does not exceed the vehicle's capacity. Constraints (5.13) prevent vehicles from being loaded in more than one facility. Constraints (5.14) makes sure that if a vehicles visits any customers, i.e. is used, it must also leave at some point, while constraints (5.15) prevent the vehicles from leaving more than once. Constraints (5.16) make sure that if a vehicle has left the production facility it cannot be loaded in the time slots after it has left. Constraints (5.17) make sure that if a vehicle leaves it must drive from a production facility to a customer. Equations (5.18) ensure that if a node is visited a vehicle must enter this node. For the customer nodes (5.18) ensure that only one vehicle can enter the node, while for the facilities they ensure that the same number of vehicles enter the facility node as the number of vehicles that visit the facility node. The continuity constraints (5.19) make sure that if a vehicle enters a node it must also exit that node. (5.19) also make sure vehicles return to their original facility.

Constraints (5.20) make sure that the time at each node is larger than the start time plus the travel time to that node from the facility. Constraints (5.21) makes sure that if i is the node that precedes j, the arrival time in j is greater than the arrival time in i plus the travel time from i to j. The time-window constraints (5.22) handle the earliest arrival time and delivery deadline in each customer node. The time constraints (5.20)-(5.21) also eliminate subtours.

5.3 Strengthening the model

The arc-flow model is solved in Xpress as a mixed integer program (MIP). The LP relaxation of the model is solved first and then the MIP is solved by the Branch and Bound (B&B) algorithm, which successively splits the feasible region into subproblems that solve a relaxation of the integer problem and provide optimistic bounds. At the same time the algorithm searches for feasible solutions which give pessimistic bounds.

To improve the performance of the B&B algorithm valid inequalities can be added to the problem. The aim is to cut away parts of the feasible region of the LP relaxation without cutting away any integer solutions, i.e. to get a better approximation of the convex hull. This is done in an attempt to narrow the solution space as much as possible so that the B&B algorithm has a smaller space to search, and will not have to go through as many subproblems (nodes) to find the optimal solution. In this way, adding valid inequalities can reduce the solution time of the problem. At the same time, adding valid inequalities increases the number of constraints, which increases the problem size and may lead to a more complex problem and complicated solution process. It is therefore necessary to find a balance between minimizing the solution space and increasing the problem size.

When generating valid inequalities the underlying structure of the problem is exploited. Valid inequalities define relations between variables that must be met in every feasible solution [Lundgren et al., 2010]. By studying the relations between the coefficient values, i.e. the input data, and the variables and constraints in our model formulation we have established relations between variables which will always hold, and from these defined valid inequalities. Different inequalities and how these influence the solution process have been analysed, leading to the conclusion that adding a valid inequality which states the minimum number of open facilities is beneficial and reduces the solution times and gap. In addition, inequalities handling the maximum number of customers that can be visited by one vehicle proved to be efficient, reducing solution times significantly. Valid inequalities (5.33)-(5.34) are therefore included in the implementation of the arc-flow model, adapted to each case. M^C is the maximum number of customers that can be visited by a vehicle and varies from case to case.

$$\sum_{i \in I^F} f_i \geq 1 \tag{5.33}$$

$$\sum_{i \in I^C} y_{ik} \leq M^C \qquad k \in K \tag{5.34}$$

By looking at the product demand and vehicle capacities, in addition to maximum route length (given by the time window between the earliest arrival and the delivery deadline), valid inequalities regarding the minimum number of vehicles needed to serve subgroups of customers can strengthen the model as well.

An important challenge in mathematical modelling is avoiding symmetrical solutions. This occurs when several solutions are mathematically different, but practically equal. In a case with a homogeneous fleet of vehicles there is no difference between vehicle 1 driving a route and vehicle 2 driving the exact same route since the vehicles have equal capacities and costs. However, these two solutions will look like two different solutions mathematically which will lead to an increase in the solution time [Baricelli et al., 1998]. For example, 7 identical vehicles leads to $7! = 5040$ model solutions for each real solution. Identical printing presses at each printing facility also increases symmetry. Symmetric solutions can be reduced by applying symmetry breaking constraints such as locking some vehicle numbers to customers. Different symmetry breaking constraints have been tested, and locking some vehicles to customers has proved to be efficient with respect to solution time and will therefore be included in the implementation of the arc-flow model.

6 Dantzig-Wolfe Decomposition

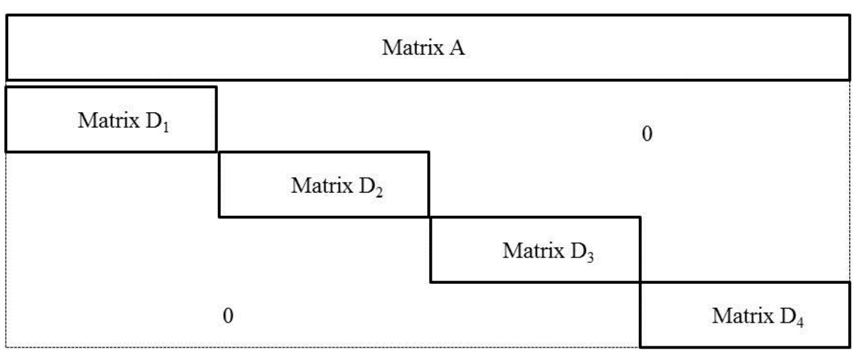
In this chapter we present the reformulation of the arc-flow model. The arc-flow model is reformulated using Dantzig-Wolfe decomposition (DWD) which results in a path-flow formulation. The model is decomposed using two different decomposition strategies which are presented in Sections 6.3 and 6.4. Before describing the decomposition strategies basic Dantzig-Wolfe principles are explained.

6.1 Theory

The Dantzig-Wolfe decomposition method was first presented by George B. Dantzig and Phillip Wolfe in 1960 as a technique for decomposing large linear problems. The method builds on the principle of alternately solving linear subproblems (SP) and a coordinating problem often known as the master problem (MP), in a finite iterative process until the optimal solution to the original problem is found. [Dantzig and Wolfe, 1960]

Decomposition methods build on the principle that if the size and complexity of a problem makes it too difficult to solve within reasonable time, many smaller typically well-structured subproblems that are coordinated by one master problem can be solved instead. These methods are well-suited for problems with constraints that naturally decompose into subproblems that define more tractable combinatorial structures, permitting more efficient solution [Vanderbeck and Savelsbergh, 2006]. See Figure 8 for an illustration of a structure that naturally decomposes into blocks.

Figure 8: *Angular block structure for constraint matrix [Lundgren et al., 2010]*



In addition to DWD, several other decomposition methods have been developed, two of the most commonly used being Lagrangean relaxation and Benders decomposition. Depending on the underlying structure of the problem these decomposition methods may be used interchangeably. DWD has been applied successfully in a variety of contexts including vehicle routing and production scheduling so we have chosen to apply this method to our model, even though e.g. Lagrangean relaxation also could have been used. In the rest of this section we will explain how DWD works and demonstrate the solution approach with a simple example.

The feasible solutions to a problem can be described in several ways, both by an outer representation using constraints, where the feasible region is described by the intersection of halfspaces, or by an inner representation as a convex combination of extreme points [Lundgren et al., 2010]. In the DWD method the MP uses interior representation. The MP consists of the objective function and the constraints that connect the subproblems. These are expressed as convex combinations of the extreme points from the subproblems.

For many problems, including all extreme points leads to an intractable amount of variables in the MP. However, it is not necessary to include all variables, as only a small subset of these will be a part of the optimal solution. Starting with a subset of the variables, a restricted master problem (RMP) can be solved. New variables are generated dynamically through an iterative process referred to as column generation. In every iteration a check is made to see if any variables not yet included in the RMP have a negative reduced cost and can improve the objective function. [Lundgren et al., 2010] The objective value in the subproblems represents the reduced cost. In each cycle the values of the dual variables from the constraints in the RMP give new objective function coefficients for each subproblem. In turn, each subproblem generates (from its optimal basic feasible solutions) new columns for the RMP. The term column refers to the information related to the new entering variable, i.e. the constraint coefficients and objective function coefficient. This process is illustrated in Figure 9.

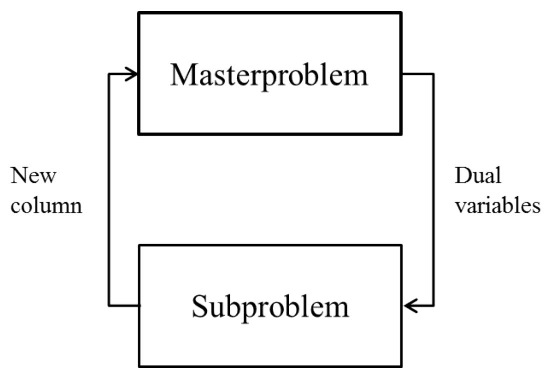


Figure 9: *Illustration of the Dantzig-Wolfe decomposition method*

To demonstrate how this works we present a simple example adapted from Lundgren et al. [2010].We start with the following LP problem (P):

$$(P) \qquad min\ z = c^T x \tag{6.1}$$

$$s.t. \qquad Ax \geq b \tag{6.2}$$

$$Dx \geq e \tag{6.3}$$

$$x \geq 0 \tag{6.4}$$

In this problem the constraints $Dx \geq e$ have a simple structure. E.g. a block angular structure, such as the one presented in Figure 8, where many of the variables in these constraints have zero as constraint coefficients. These constraints can naturally be decomposed into subproblems that are computationally efficient to solve. Constraints $Ax \geq b$ however, are complicating or connecting constraints and thereby destroy the simple structure of the problem.

As explained above, solutions can be described by an inner or outer representation. When using the DWD method the constraints in the MP are expressed as convex combinations of the extreme points in the subproblems, i.e. inner representation. All points x in the set $X_D = \{x|Dx \geq e, x \leq 0\}$ can be written as a convex combination of the extreme points to the set X_D, denoted $x^{(1)}, x^{(2)}...x^{(p)}$:

$$x = \sum_{j=1}^{p} x^{(j)}\lambda_j, \qquad \sum_{j=1}^{p} \lambda_j = 1 \qquad and \qquad \lambda_j \geq 0, \qquad j = 1, ..., p \tag{6.5}$$

Substituting the inner representation of x in to (P) we get the master problem:

$$(MP) \qquad max \quad z = \sum_{j=1}^{p} (c^T x^{(j)})\lambda_j \tag{6.6}$$

$$s.t. \qquad \sum_{j=1}^{p} (Ax^{(j)})\lambda_j \geq b \tag{6.7}$$

$$\sum_{j=1}^{p} \lambda_j = 1 \tag{6.8}$$

$$\lambda_j \geq 0, \qquad j = 1, ..., p \tag{6.9}$$

(MP) has fewer constraints than (P) now that $Dx \geq e$ has been removed. However, the MP has many more variables; one variable for every extreme point in X_D. There may be too many extreme points to handle efficiently and it may also be difficult to know what all the extreme points are. In addition, we know that most of the extreme points will have their associated variable equal to zero in an optimal solution. [Barnhart et al., 2000] If we assume that we know a small subset of q extreme points we can, however, solve a RMP using only the known extreme points to find a feasible solution:

$$(RMP) \qquad max \quad z = \sum_{j=1}^{q} (c^T x^{(j)})\lambda_j \tag{6.10}$$

$$s.t. \qquad \sum_{j=1}^{q} (Ax^{(j)})\lambda_j \geq b \qquad |v \tag{6.11}$$

$$\sum_{j=1}^{q} \lambda_j = 1 \qquad |u \tag{6.12}$$

$$\lambda_j \geq 0, \qquad j = 1, ..., q \tag{6.13}$$

Where v and u are the dual variables connected to the constraints (6.11) and (6.12). If the optimal solution to the RMP is given by $\bar{\lambda}_j$ we know that the solution

$$\bar{x} = \sum_{j=1}^{q} x^{(j)} \bar{\lambda}_j \tag{6.14}$$

is feasible, but there might be other extreme points in $j = q + 1, ..., p$ that are better. To verify if the solution is optimal we need to check if any other solution has a negative reduced cost, $\bar{c}_j < 0$. This is done by solving the subproblem, which is a separation problem for the dual LP, with the aim of searching for the extreme point with the minimal reduced cost.

$$(SP) \qquad min\ (c^T - \bar{v}^T A)x - \bar{u} \tag{6.15}$$

$$Dx \geq e \tag{6.16}$$

$$x \geq 0 \tag{6.17}$$

The SP objective function represents the reduced cost $\bar{c}_j$. The coefficients $\bar{v}$ and $\bar{u}$ are the values on the dual variables connected to the constraints (6.11) and (6.12) in the RMP.

If no negative reduced cost is found there are no other extreme points that will improve the solution in the RMP. If a solution is found where the reduced cost is negative this extreme point, or column, is added to the RMP. The RMP and SP are solved iteratively until no more columns with negative reduced costs are found and the problem has been optimized. In this way many of the columns can be left out of the MP if there are too many to handle efficiently, and only the most promising columns will be generated through the SP.

It is important to note that the DWD only guarantees optimality for linear programs and can therefore only solve the LP relaxation of integer programs (IP). The columns are generated based on dual variables and reduced costs for continuous variables and are therefore not necessarily the most profitable when integrality is required. It is possible to apply a Branch and Bound algorithm which may give feasible and in some cases even optimal solutions, but B&B does not guarantee optimality for the IP.This is due to the fact that the columns generated to solve the LP might not be sufficient to solve the problem with integer restrictions. Therefore new columns need to be generated in every node in the B&B tree. This method is called Branch and Price, and can be used to solve IP models to optimality. Branch and Price applies column generation throughout the B&B tree, branching when no columns have negative reduced costs and the LP solution does not satisfy the integrality conditions [Barnhart et al., 2000]. As a heuristic, it is possible to generate a large pool of initial columns, and based on this pool and the columns found in the column generation, B&B can be applied to find feasible solutions [Lundgren et al., 2010].

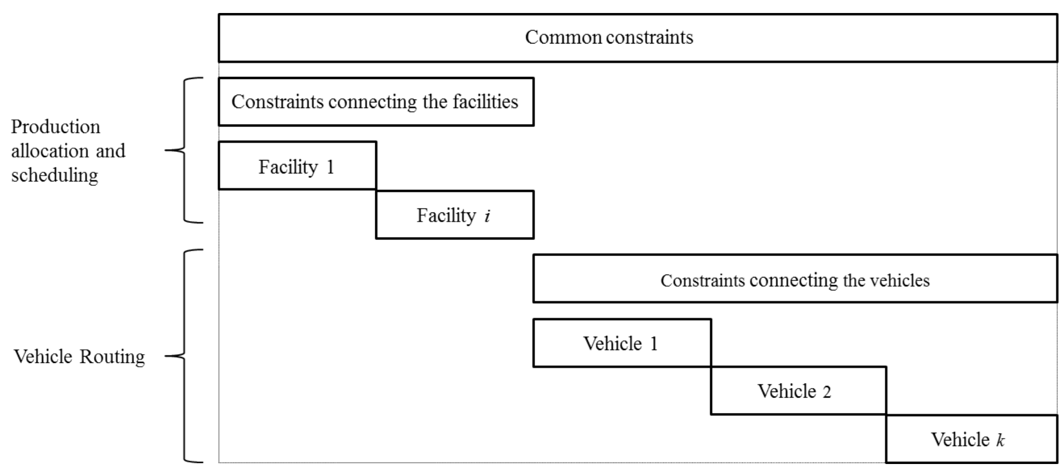
Although DWD cannot guarantee optimality for IP models it provides a lower bound (for minimization problems) on the objective value that may be a stronger optimistic bound than the solution to the LP relaxation of the original problem. In this way, using DWD together with B&B can generate good optimistic and pessimistic bounds respectively.

6.2 Decomposition strategies

The arc-flow model presented in Chapter 5 can be solved directly in Xpress, but can only be solved to optimality for relatively small problem instances due to its complexity. To solve larger, more realistic instances a reformulation and decomposition method can be used. We have developed two models by reformulating the arc-flow formulation and decomposing the problem into subproblems using the DWD method. In doing this we wish to investigate if stronger bounds can be found for the LP relaxation and larger problem instances solved.

As mentioned earlier, the PASPR integrates production allocation and scheduling (PAS) with vehicle routing (VR). By separating the constraints according to whether they belong to the PAS or VR, and studying the structure of the problem it is evident that the PAS is easily decomposed into subproblems for each facility, and that most of the VR constraints are local with respect to each vehicle. The latter implies that the VR can be formulated using a path flow formulation [Andersson et al., 2011b] with subproblems for each vehicle. The grouping of constraints can be found in Appendix A. Figure 10 illustrates the structure of the PASPR, where the rectangles represent sets of constraints.

Figure 10: *The structure of the PASPR*



The common constraints are the constraints that connect the PAS and VR. The loading variables q_{ipkt}, which determine how much of a product is loaded in each vehicle in each time slot, are connected to the leaving variables, x_{kt}, that determine in which time slot a vehicle leaves. The loading variables are also connected to y^N_{ik} and y^C_{ikp}, which determine which customers a vehicle visits and which products it delivers.

The constraint sets that connect the PAS and VR through the loading variables q_{ipkt} and the visiting variables y^C_{ikp} and y^N_{ik} are (6.18) and (6.19). The former make sure vehicles are loaded with all the demand in their route and the latter prevent vehicles from being loaded in more than one facility.

$$\sum_{i \in I^F} \sum_{t \in T} q_{ipkt} - \sum_{i \in I^C} D_{ip} y^C_{ipk} \geq 0 \qquad k \in K, p \in P \tag{6.18}$$

$$Q_k y^N_{ik} - \sum_{t \in T} \sum_{p \in P} q_{ipkt} \geq 0 \qquad i \in I^F, k \in K \tag{6.19}$$

In addition to the common constraints that connect the PAS and VR, there are constraints that connect the facilities in the PAS and the vehicles in the VR. There is only one set of constraints that connects the facilities. Constraints (6.20) make sure that if a vehicle has left any production facility it cannot be loaded in the time slots after it has left. (6.20) also connect the PAS and VR through the loading variables q_{ipkt} and leaving variables x_{kt}.

$$Q_k(1 - x_{kt}) - \sum_{i \in I^F} \sum_{\tau = t+1}^{T} \sum_{p \in P} q_{ik\tau p} \geq 0 \qquad k \in K, t \in T \tag{6.20}$$

The only constraints connecting the vehicles are (6.21) which ensure that all customer nodes are visited by at least one vehicle, and (6.22) which make sure all products with demand in a node are delivered.

$$\sum_{k \in K} y^N_{ik} \geq 1 \qquad i \in I^C \tag{6.21}$$

$$\sum_{k \in K} y^C_{ikp} = 1 \qquad i \in I^C, p \in P | D_{ip} > 0 \tag{6.22}$$

The structure of the problem presented in Figure 10 naturally leads to three alternative decomposition strategies which are presented in Table 2.

All of the alternatives have the common constraints in the coordinating master problem, as well as the constraints that connect the facilities and vehicles in the PAS and VR respectively. The first alternative is to decompose the problem into two subproblems; one for the PAS which is solved for each facility and one for the VR which is solved for each vehicle. Alternative 2 is to include the PAS constraints in the master problem and have the VR in the subproblem, and vice versa for Alternative 3.

We have tested two of these strategies, Alternative 1 and 2. These are referred to as Decomposition with two subproblems (D2SP) and Decomposition with one subproblem (D1SP) in the rest of the thesis and are described in detail in sections 6.3 and 6.4, respectively.

6.3 Decomposition with two subproblems

Using the decomposition strategy with two subproblems the model is reformulated and decomposed so that there are PAS subproblems (PAS-SP), VR subproblems (VR-SP) and a MP consisting of the objective function and all connecting constraints.

Table 2: Alternative Decomposition Strategies

	Master problem	**Subproblems**
Alternative 1 (D2SP)	Common and all connecting constraints	PAS VR
Alternative 2 (D1SP)	PAS, common and all connecting constraints	VR
Alternative 3	VR, common and all connecting constraints	PAS

As mentioned in the previous section, the majority of the routing constraints do not include interaction between the vehicles so a path-flow model is formulated to take advantage of the underlying structure when the problem is decomposed into SPs for each vehicle. For each VR-SP we want to find a feasible path or route with respect to the delivery time windows and quantity loaded in the vehicle so that the load does not exceed the vehicle capacity. The VR determines not only the geographical routing, but also which products are delivered to the customers visited. Each feasible combination of leaving times, customers visited and products delivered can be called a delivery pattern. The VR-SP can be formulated and solved in two different way. The first alternative is to determine both the geographical routing and delivery of products for each vehicle. The second alternative is to pre-generate feasible geographic routes, and solve the VR-SP for each vehicle and route in order to determine only the delivery pattern.

Pre-generating all feasible routes can become intractable if the number of customers is large, but by adding a dominance function to the algorithm many feasible routes can be eliminated so the number of routes in our case should be manageable. We have chosen to pre-generate the routes and will therefore formulate the MP and VR-SP accordingly. The process for pre-generating routes is described in detail in Section 7.

The VR-SP will then be solved for each vehicle and route in order to generate new delivery patterns that can be added to the RMP. The number of possible patterns is very large but through column generation only the most promising patterns are generated. We introduce delivery pattern variables λ_{krw} for each vehicle and route, where w denotes the pattern number. These variables are also referred to as route variables. The decision variables in the VR-SP, y_{ipkr}, are similar to the delivery variables y^C_{ikp} in the arc-flow formulation but are also defined for each route. These are binary and equal to one if vehicle k delivers product p to customer i using route r.

For the facilities there exists many feasible combinations of production schedules. A production schedule consists of all the production and loading into vehicles at one facility. The PAS-SP is solved for each facility with the aim of generating improved schedules. If improving schedules are found these are added to the RMP. We define new variables for each facility schedule, θ_{is}. These are equal to 1 if schedule s is used in facility i.

Before presenting the mathematical formulations of the MP, PAS-SP and VR-SP we will describe the connection between the MP and SP variables. As explained in section 6.1 the constraints in the MP are expressed as convex combinations of the solutions from the SPs. We will therefore reformulate the connecting constraints using the new variables λ_{krw} and θ_{is}.

The new parameters for the interior representation:

Y_{ipkrw}	1 if vehicle k delivers product p to customer i using route r and pattern w.
Q_{ipkts}	Quantity of product p loaded to vehicle k at facility i in time slot t with schedule s.
T^F_{ks}	Time slot when vehicle k is finished loading using schedule s

$$\sum_{w \in W} Y_{ipkrw}\lambda_{krw} = y_{ipkr} \qquad i \in I^C, p \in P, k \in K, r \in R \tag{6.23}$$

$$\sum_{s \in S} Q_{ipkts}\theta_{is} = q_{ipkt} \qquad i \in I^F, p \in P, k \in K, t \in T \tag{6.24}$$

$$\sum_{s \in S} T^F_{ks}\theta_{is} = t^F_k \qquad i \in I^F, p \in P, k \in K, t \in T \tag{6.25}$$

When the SPs are solved new columns are added to the coefficient matrices in the RMP.

6.3.1 Master Problem

In this section we present the MP for D2SP. We start by defining sets and indices for the entire problem and parameters and decision variables for the MP before presenting the objective function and constraints.

Sets and indices

I	Set of nodes i
I^C	Subset of customer nodes i
I^C_r	Customers visited in route r
I^F	Subset of production facility nodes i
M	Set of printing presses $m = 1, \ldots, N^M$
K	Set of vehicles k
P	Set of products p
R	Set of routes r
R_f	Set of routes starting in facility i
S	Set of schedules s
T	Set of time slots $t = 1, \ldots, N^T$
W	Set of product patterns w

Parameters

C^R_{kr}	Cost of vehicle k driving route r
C^S_{is}	Cost of facility i using schedule s
D_{ip}	Demand of product p at node i
T^F_{ks}	Time slot when vehicle k is finished loading on schedule s
T^S_{kr}	Time slot when vehicle k at the latest can start route r
Q_{ipkts}	Quantity of product p loaded to vehicle k at facility i in time slot t with schedule s
Q_{iks}	1 if vehicle k is loaded at production facility i with schedule s
Y^N_{ir}	1 if node i is visited on route r
Y_{ipkrw}	1 if product p is delivered to customer i by vehicle k on route r with pattern w, 0 otherwise

Decision Variables

λ_{krw}	Binary variable 1 if vehicle k drives route r with pattern w
θ_{is}	Binary variable 1 if facility i uses schedule s

$$min\ z = \sum_{k\in K}\sum_{r\in R}\sum_{w\in W} C^R_{kr}\lambda_{krw} + \sum_{i\in I^F}\sum_{s\in S} C^S_{is}\theta_{is} \tag{6.26}$$

$$\beta_{jpk}| \quad \sum_{t\in T}\sum_{s\in S} Q_{jpkts}\theta_{js} - \sum_{i\in I^C}\sum_{r\in R_f}\sum_{w\in W} D_{ip}Y_{ipkrw}\lambda_{krw} \geq 0 \quad j \in I^F, p \in P, k \in K \tag{6.27}$$

$$\alpha_{ip}| \quad \sum_{k\in K}\sum_{r\in R}\sum_{w\in W} Y_{ipkrw}\lambda_{krw} \geq 1 \quad i \in I^C, p \in P|D_{ip} > 0 \tag{6.28}$$

$$\gamma_{ik}| \quad \sum_{r\in R_f}\sum_{w\in W} Y^N_{ir}\lambda_{krw} - \sum_{s\in S} Q_{iks}\theta_{is} \geq 0 \quad i \in I^F, k \in K \tag{6.29}$$

$$\epsilon_{ik}| \quad \sum_{r\in R_f}\sum_{w\in W} T^S_{kr}\lambda_{krw} - \sum_{s\in S} T^F_{ks}\theta_{is} \geq 0 \quad i \in I^F, k \in K \tag{6.30}$$

$$\eta_k| \quad \sum_{r\in R}\sum_{w\in W} \lambda_{krw} \leq 1 \quad k \in K \tag{6.31}$$

$$\mu_i| \quad \sum_{s\in S} \theta_{is} \leq 1 \quad i \in I^F \tag{6.32}$$

$$\lambda_{krw} \in \{0,1\} \quad k \in K, r \in R, w \in W \tag{6.33}$$

$$\theta_{is} \in \{0,1\} \quad i \in I^F, s \in S \tag{6.34}$$

The objective function (6.26) minimizes the total cost of all the routes and schedules that are chosen. The route cost comprises the vehicle cost, labour costs for the driver and transportation costs. These are given for each route from the pre-generation. The schedule cost consists of facility costs and plate costs. Constraints (6.28) makes sure that all demand is delivered, while (6.27) assures this demand to be loaded as well. A vehicle can only be loaded in one facility, which is constrained by (6.29). (6.30) ensures that all the products in a vehicle are loaded before that vehicle starts its route. (6.31) - (6.34) make sure that every vehicle and every printing facility is assigned either zero or one delivery pattern or schedule respectively. The values of the dual variables connected to the constraints in the MP, α_{ip} - μ_i give the objective value coefficients in the subproblems.

The reduced master problem, RMP, is merely the MP solved while only looking at a subset of all facility schedules and delivery patterns. The sets of vehicles K, routes R, patterns W and schedules S are then denoted by K^*, R^*, W^* and S^* instead.

6.3.2 Vehicle Routing Subproblem

The VR-SP decomposes into one problem for each vehicle and each pre-generated route. For each vehicle and route the VR-SP searches for the pattern with the minimum reduced cost. If the reduced cost is negative a new delivery pattern is added to the RMP.

Parameters

C^R_{kr}	Cost of vehicle k driving route r
H_k	Capacity of vehicle k
Y_{ir}	1 if node i is in route r

Decision Variables

y_{ipkr}	Binary variable 1 if product p is delivered to customer i by vehicle k on route r
$\bar{c}_{kr}$	Reduced cost of vehicle k using route r

$$min\ \bar{c}_{kr} = C^R_{kr} - \sum_{i \in I^C} \sum_{p \in P} \bar{\alpha}_{ip} y_{ipkr} + \sum_{i \in I^C} \sum_{p \in P} \bar{\beta}_{jpk} D_{ip} y_{ipkr} - \bar{\gamma}_{jk} - T^S_{kr} \bar{\epsilon}_{jk} - \bar{\eta}_k \tag{6.35}$$

$$\sum_{p \in P} y_{ipkr} \geq Y_{ir} \qquad i \in I^C_r \tag{6.36}$$

$$\sum_{i \in I^C_r} \sum_{p \in P} D_{ip} y_{ipkr} \leq H_k \tag{6.37}$$

$$y_{ipkr} \in \{0, 1\} \qquad i \in I, p \in Pk \in K, r \in R \tag{6.38}$$

Note that the index j here refers to the facility that route r leaves from. Constraints (6.36) make sure a product is delivered in each node which is visited in the route the problem is solved for. (6.37) makes sure that the products delivered in a delivery pattern do not exceed the capacity of the vehicle. The rest of the VR constraints, such as time window constraints, are handled in the pre-generation of the routes.

The variables y_{ipkr} return which products are delivered to customer i by vehicle k in route r. This constitutes a delivery pattern w for the route r and vehicle k. This information is conveyed to the RMP as a new column in Y_{ipkrw} if the new delivery pattern has a negative reduced cost.

6.3.3 Production Allocation and Scheduling Subproblem

The PAS-SP decomposes into one problem for each facility. The PAS-SP finds the loading schedules s with minimal reduced cost for each printing facility, and if the reduced cost is negative a new schedule is added to the RMP.

Parameters

C^F	Facility cost
C^P	Cost of producing printing plates
H_k	Capacity of vehicle k
M_i^L	Maximum quantity that can be loaded in a time slot at facility i
R_{imp}	Production rate at facility i on press m for product p
S_{im}	The number of time slots required for a product change on press m in facilty i

Decision Variables

$\bar{c}_{is}$	Reduced cost of facility i using schedule s
g_{impt}	Binary variable 1 if product p is produced on press m in facility i in time slot t
h_{ip}	Number of printing plate sets needed to print product p at facility i
q_{ipkt}	The quantity of product p loaded onto vehicle k at production facility i in time slot t
t_{kt}^L	Binary variable 1 if vehicle k is loaded in time slot t
t_k^F	Time slot when vehicle k is finished loading

$$min\ \bar{c}_{is} = C^F + \sum_{p \in P} C^P h_{ip} - \sum_{p \in P} \sum_{k \in K} \sum_{t \in T} \bar{\beta}_{ipk} q_{ipkt} + \sum_{p \in P} \sum_{k \in K} \sum_{t \in T} \bar{\gamma}_{ik} q_{ipkt} + \sum_{k \in K} \bar{\epsilon}_{ik} t_k^F - \bar{\mu}_i \quad (6.39)$$

$$h_{ip} - \sum_{m \in M} g_{impt} \geq 0 \qquad p \in P, t \in T \qquad (6.40)$$

$$\sum_{p \in P} g_{impt} \leq 1 \qquad m \in M, t \in T \qquad (6.41)$$

$$\sum_{t \in T} \sum_{p \in P} q_{ipkt} \leq H_k \qquad k \in K \qquad (6.42)$$

$$S_{im}(1 - g_{imp(t-1)}) - \sum_{\rho \in P \backslash p} \sum_{\tau = t}^{t+S_{im}-1} g_{im\rho\tau} \geq 0 \qquad m \in M, p \in P, t = 2, \ldots, N^T \qquad (6.43)$$

$$\sum_{m \in M} R_{imp} g_{impt} - \sum_{k \in K} q_{ipkt} \geq 0 \qquad p \in P, t \in T \qquad (6.44)$$

$$M_i^L t_{kt}^L - \sum_{p \in P} q_{ipkt} \geq 0 \qquad k \in K, t \in T \qquad (6.45)$$

$$\sum_{p \in P} q_{ipkt} - t_{kt}^L \geq 0 \qquad k \in K, t \in T \qquad (6.46)$$

$$t_k^F - \tau t_{k\tau}^L \geq 0 \qquad k \in K, \tau \in T \qquad (6.47)$$

$$g_{impt} \in \{0, 1\} \qquad i \in I, m \in M, t \in T, p \in P \qquad (6.48)$$

$$t_{kt}^L \in \{0, 1\} \qquad k \in K, t \in T \qquad (6.49)$$

$$q_{ipkt} \geq 0 \qquad i \in I, p \in P, k \in K, t \in T \qquad (6.50)$$

$$h_{ip} \geq 0\ and\ integer \qquad i \in I, p \in P \qquad (6.51)$$

$$t_k^F \geq 0\ and\ integer \qquad k \in K \qquad (6.52)$$

The constraints in the PAS-SP are the remaining constraints from the arc-flow model not included in the MP or the VR-SP. In addition we have added (6.42) so that no vehicle is loaded with more than its capacity. (6.45)-(6.47) replace (5.16) in the arc-flow model. These constraints make sure the finish time t_k^F of a vehicle is correct. The finish time returns the time slot in which vehicle k can leave using a schedule. If the schedule has a negative reduced cost the finish time is conveyed to the master problem by adding a new column to T_{ks}^F.

q_{ipkt} returns how much of product p is loaded to vehicle k in time slot t at facility i. Considering all time slots at one facility this gives the loading schedule which is communicated to the master problem as a new column in Q_{ipkts}. This enables the RMP to coordinate that the correct amount is loaded to the vehicles that are used according to which customers the vehicle visits in its route.

6.4 Decomposition with one subproblem

This decomposition strategy is denoted by D1SP. It includes the PAS and connecting constraints in the master problem and the VR in the subproblem. In this way the production allocation and scheduling is now decided in the MP as well as which delivery patterns to use. Dual information from the connecting constraints is sent to the VR-SP in the same way as before and new delivery patterns are generated in the VR-SPs. The VR-SP is identical to the one presented in section 6.3.2 for D2SP, and many of the constaints in the MP will be identical to the ones in D2SP. We therefore only present the new MP constraints here.

Instead of using schedule variables and the interior representation we can now use the original loading and time variables in the MP. The objective function changes to (6.53), which replaces schedule cost with the cost of printing plates and facility cost. Constraints (6.28) and (6.31) from D2SP are identical for D1SP. Constraints (6.27)-(6.30) are replaced by (6.54)-(6.56) in order to use the original loading and time variables. The new binary variable q_{ik} is 1 if vehicle k is loaded at production facility i, constraints (6.57) are added to ensure this. (6.58) are also added to ensure that if anything is produced in a facility, that facility must be open.

$$min\ z = \sum_{i \in I^F} C^F f_i + \sum_{i \in I^F} \sum_{p \in P} C^P h_{ip} + \sum_{k \in K} \sum_{r \in R} \sum_{w \in W} C^R_{kr} \lambda_{krw} \tag{6.53}$$

$$\sum_{t \in T} q_{jpkt} - \sum_{i \in I^C} \sum_{r \in R_f} \sum_{w \in W} D_{ip} Y_{ipkrw} \lambda_{krw} \geq 0 \qquad j \in I^F, p \in P, k \in K \tag{6.54}$$

$$\sum_{r \in R_f} \sum_{w \in W} Y^N_{ir} \lambda_{krw} - \sum_{s \in S} q_{ik} \geq 0 \qquad i \in I^F, k \in K \tag{6.55}$$

$$\sum_{r \in R_f} \sum_{w \in W} T^S_{kr} \lambda_{krw} - t^F_{ik} \geq 0 \qquad i \in I^F, k \in K \tag{6.56}$$

$$q_{ik} - g_{impt} \geq 0 \qquad i \in I^F, m \in M, p \in P, k \in K, t \in T \tag{6.57}$$

$$f_i - g_{impt} \geq 0 \qquad i \in I^F, m \in M, p \in P, t \in T \tag{6.58}$$

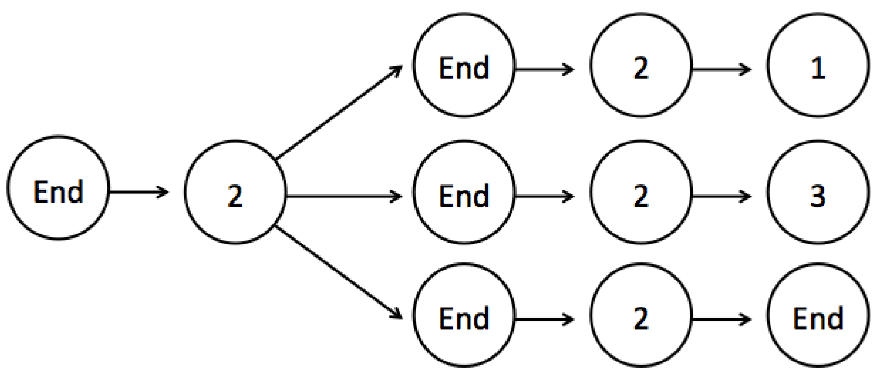
Constraints (6.40)-(6.52) from the PAS-SP for D2SP will all be included in the MP for D1SP, but are declared for all facilities. These constraints do not send any dual information to the VRP but including them in the MP will affect the dual information sent from the connecting constaints. The full D1SP model can be found in Appendix B.

7 Pre-generation of Routes

In this chapter we describe how the routes have been pre-generated. In order to reduce the complexity in the VRP-SP we have generated all the possible routes a priori. This can be done since a Shortest Path Problem with Time Windows (SPPTW) for each vehicle can be extracted from our vehicle routing problem. The SPPTW does not decide which products to deliver, but finds the optimal geographic routes with respect to the time windows. A label correcting algorithm combines arcs to form feasible routes and updates the label's length and time dynamically. The labels in each node are not saved, but updated, hence the algorithm is label correcting instead of label setting. Length and time can also be seen as resources where length is unconstrained, but time is a limited resource. The lower bounds for both are given by a resource extension function (REF) at every node [Irnich and Desaulniers, 2014].

There is a definite deadline at every customer, but the finish time of producing the products for a given vehicle may vary. Therefore the pre-generation uses backward-extension from the end facility to calculate a latest start time for the route. Partial routes can be extended with a customer not yet visited to form a new partial route, or with the end facility to form a complete route. Figure 11 shows a small example which illustrates all the possibilities for extending a partial route if there are three customers in total. Note that since we use backward-extension this route will be reversed. The rightmost 'End' refers to the route origin, which is the same facility as the route was extended from.

Figure 11: *Possible extensions of a partial schedule. Inspired by Andersson et al. [2011a]*



The pre-generation returns all feasible routes which comply with the time window constraints. Routes that are sub-optimal to other comparable routes are excluded through a dominance function. If two routes visit the same customers, but one of them is both shorter and faster, the other route is dominated and removed from the set of routes. Both partial and complete routes can be dominated. Each node has an earliest possible arrival that may lead to waiting on a route, and therefore the algorithm compares both distance and time in the dominance function. Each node has a common deadline for all the products with demand, but the deadlines in the different nodes can vary. In addition to the dominance function we have added constraints that limit the number of customers visited on a route. This reduces both the time needed to generate routes and the number of routes generated, and thus the number of VR subproblems in the path-flow models. This is further described in Section 9.4.

Distances and times between nodes are found using Google Maps and the data is extracted using a Python script. The pre-generation algorithm is written in C++ and implemented in Visual Studio 2010. Below is a pseudo-code that describes the main steps.

---

forall *Facilities* **do**
    Create root-node and add to PartialRoutes
    while *PartialRoutes is not empty*
        Delete first route in PartialRoutes and call it Route
        forall *Nodes* **do**
            if *Node is Customer and not on Route* **then**
                if *possible new Route time > Earliest arrival at Customer* **then**
                    NewRoute=Route extended with Customer and updated Route length
                    NewRoute time=minimum of(Latest arrival, possible new Route time)
                    Add NewRoute to PartialRoutes
            else if *Node is Facility*
                Extend Route with Facility and update Route time and length
                Add Route to CompleteRoutes
        end-forall
        forall *PartialRoutes* **do**
            if *Current last customer in two partial routes are equal* **then**
                if *The two partial routes have visited the same customers* **then**
                    if *Route length and time are higher for Route A* **then**
                    Delete Route A
        end-forall
    end-while
    forall *CompleteRoutes* **do**
        if *Two complete routes have visited the same customers* **then**
            if *Route length and time are higher for Route A* **then**
            Delete Route A
    end-forall
end-forall
return *CompleteRoutes*

Since we use backward-extension, updating of the time label is opposite of what may seem natural.

The pre-generation results in the following data as input to the path-flow models:

R	Set of routes r
I_r^C	Customers visited on route r
C_{kr}^R	Cost of vehicle k driving route r
T_{kr}^S	Time slot when vehicle k at the latest can start route r
Y_{ir}	1 if node i is in route r

8 Case Description

In this chapter we describe the case that is used in the computational study, for both the technical and economical analysis. The case is a simplification of a real case from the Norwegian newspaper industry in the area around Oslo and South-Eastern Norway. Necessary input data are also presented.

8.1 South-Eastern Norway

The two largest printing facilities in Eastern Norway are considered, each owned and operated by the two largest media groups in the Norwegian newspaper industry, Amedia and Schibsted. The Amedia printing facility we consider is located at Stokke, right outside Tønsberg, approximately 110 kilometers south of Oslo. The Schibsted printing facility is located in Nydalen in Oslo. Both media groups own and manage other printing facilities in Norway, but we limit our case to these two.

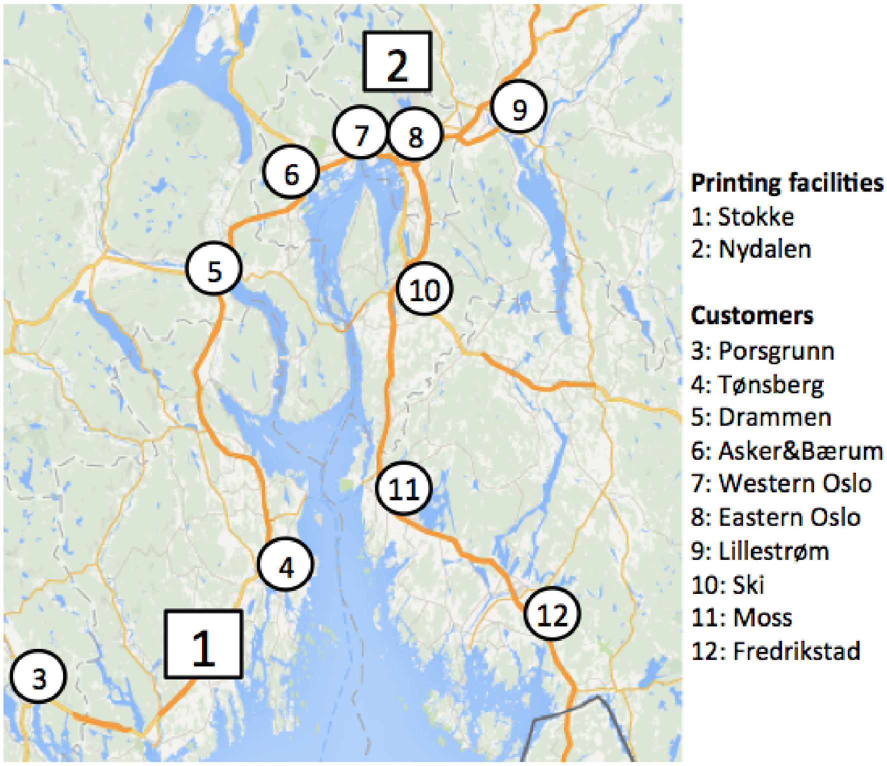
Amedia and Schibsted print many of their newspaper titles in Stokke and Nydalen. We have chosen to consider a subset of seven of the largest editions. The editions are listed in Table 3 together with the product number used in our model and owner. Amedia's editions are mostly local newspapers with demand restricted to specific geographical areas, while Schibsted's are larger, national newspapers with more widespread geographical demand.

Table 3: *Newspaper products included in case*

Product	Newspaper	Short	Owner
1	Aftenposten	AP	Schibsted
2	Drammens Tidende	DT	Amedia
3	Fredriksstad Blad	FB	Amedia
4	Moss Avis	MA	Amedia
5	Tønsbergs Blad	TB	Amedia
6	Varden	V	Amedia
7	Verdens Gang	VG	Schibsted

Geographically spread demand for each of these editions have been aggregated to form drop-off points in the first echelon distribution to customer nodes. We consider the demand in the South-Eastern part of Norway and have chosen customer nodes in large cities which best represent the geographical spread of demand in this part of the country. South-Eastern Norway is here defined to include Østfold, Akershus, Oslo, Vestfold and lower parts of Buskerud and Telemark. The customer nodes and printing facility locations can be seen in Figure 12. Oslo is split into two customer nodes due to its high demand compared to the other cities.

Figure 12: *Customers and facilities in case*



Instances

For comparison of the different models we use two different instances of the case described above. Instance N2 is the same size as presented, and instance N1 is a smaller version with two less customers. In this instance customer 6 and 9 (Asker & Bærum and Lillestrøm) are removed. The newspaper demand at these nodes is also removed from the production part of the problem. For both instances we have locked one vehicle to visit and deliver all the demand in Western Oslo and one vehicle to do the same in Eastern Oslo. These vehicles are routed from the production facility in Nydalen in Oslo. This reduces the routing part of the problem to include 6 and 8 customers for N1 and N2, respectively. The demand in both Oslo nodes consists of only Aftenposten and VG, and this is included in the production part of the problem. We have locked the vehicles to reduce the problem sizes to further reduce solution times. In the arc-flow model the vehicles are locked with constraints. For the path-flow models Western and Eastern Oslo are removed from the pre-generation of routes, and two routes which only visit either Western or Eastern Oslo are added. These routes are locked to two vehicles with contstraints in Xpress. Locking these vehicles to drive from Nydalen means that this facility must be used. This is a valid inequality for the larger instance N2, due to low production rates at the facility in Stokke. In the smaller instance it is a simplification of the problem, but since this instance is only used for comparative purposes between the models it will not affect our results.

8.2 Input data

The data which has been used in the implementation of the model is based on information from sources in the Norwegian newspaper industry, publicly available information and some estimates. Since parts of the data we have used are based on second hand sources and estimates, and the case itself is scaled down from a real life scenario, the resulting cost picture might be inaccurate. However, our intention is not to carry out an extensive economic analysis of the newspaper industry supply chain. We wish to demonstrate what the relative effects of e.g. cooperation and moving newsroom deadlines would be, in addition to showing how the model can be used as an economic support tool in decision making.

Demand and deadlines

Distribution Innovation LC has provided us with demand data for all the newspaper titles considered for each zip code in the South-Eastern part of Norway. Demand has been aggregated to the closest customer nodes in our case. The resulting demand matrix is shown in Table 4. The demand is for an average day of the week.

Table 4: *The number of newspapers of each edition demanded at the different customers*

	AP	DT	FB	MA	TB	V	VG	Total
Porsgrunn	5494	0	0	0	0	14987	10735	**31216**
Tønsberg	8827	0	0	0	22922	0	11990	**43739**
Drammen	8810	21130	0	0	0	0	11755	**41695**
Asker&Bærum	30796	5136	0	0	0	0	11126	**47058**
Western Oslo	43590	0	0	0	0	0	18280	**61870**
Eastern Oslo	43590	0	0	0	0	0	18280	**61870**
Lillestrøm	11281	0	0	0	0	0	8587	**19868**
Ski	10583	0	0	0	0	0	6404	**16987**
Moss	8115	0	0	11064	0	0	8957	**28136**
Fredrikstad	7956	0	14755	0	0	0	10961	**33672**
Total	**179041**	**26266**	**14755**	**11064**	**22922**	**14987**	**117075**	**386110**

Production of this demand cannot start before the newsroom deadline which on average is at 9 PM. The time window for delivery at the customers is between 12 AM and 4 AM [Norvik and Urdal, 2014]. Our model allows for differentiation of the newsroom deadlines for different products and time windows for delivery for different customers, but in the base case we use the same deadlines for all products and customers.

Production

As mentioned in Chapter 2 there are both capital and operational costs to consider when looking at the total cost picture for a printing facility. Capital costs are a very complex matter which depends on several factors like value of real estate, value of equipment and interest rate among others. If one where to consider the shutdown of a facility it would be a demanding task to get an accurate estimate of the consequences. There would be potential earnings based on sales or ended leases of property and equipment, but production facilities and printing presses and other equipment are not very liquid assets so a proper market price could be hard to obtain. In addition there would be decommissioning costs since a printing facility most likely is not sold as is. It is not within the scope of this thesis to consider these potential earnings and costs. However, it is fair to assume that decommissioning costs equals potential earnings, i.e. the capital costs of keeping a facility open are zero [Norvik and Urdal, 2014].

The operational costs connected to the production of newspapers are somewhat easier to analyze since these are real costs payed for everyday by the media groups. Since we are considering where to allocate production it is only interesting to look at the differences in costs resulting from different allocations. It is assumed that the total amount of labor, material and utility costs connected to the printing of newspapers itself are constant, since there is a constant demand of newspapers to be produced. These costs are also assumed to be equal in Stokke and Nydalen. The difference in cost of production arises if it is necessary to produce the same product at different presses or facilities at the same time. If a product is printed in multiple locations, multiple sets of printing plates must be made for that product. The costs associated with producing printing plates are material costs, labor and machine costs. Amedia and Schibsted operate with small variations in these costs, but for an average newspaper total printing plate costs can be assumed to be 4000 NOK [Vestskogen and Melby, 2014].

The printing presses at Nydalen are equal and can realistically print 60000 VG in one hour [Schibsted, 2014]. We assume that the newspapers we consider are printed at the same rate. Realistic print rates at Nydalen are 75% of the maximum theoretical print rates and we assume this to be true for Stokke as well. The presses at Stokke can then print 37500 newspapers per hour [Amedia, 2014]. The presses at Stokke are also equal. We consider a little less than half of the total demand of newspapers produced in Stokke and Nydalen, so in our case we assume that we have half of the installed capacity at our disposal, i.e. two presses at Stokke and two presses at Nydalen. Nydalen actually has five presses, but two presses is a better approximation since we consider less than half of the total demand produced at the two facilities.

The changeover time between different products is, as mentioned in Chapter 4, very difficult to estimate. However, an average changeover usually takes about 30 minutes [Norvik and Urdal, 2014]. For our models a time slot size of 30 minutes is suitable with with respect to solution time, and is a good fit when considering the product demand and print rates as well. Consequently a changeover requires one time slot in our model. We assume changeover times to be equal for all presses and facilities.

Vehicle Routing

Many different types of vehicles are used for transportation of newspapers, from small personal cars to large trucks, depending on how many newspapers are needed for the route. For the first echelon distribution to drop-off points it is common to use a medium sized trucks with a loading capacity of 8000 kg. We have therefore chosen to use this type of vehicle for all of the vehicle fleet. Based on the average weight of one newspaper page and the average number of pages in the editions we consider, the vehicle capacity given in number of newspapers is found. Input data for these calculations are given in Table 5.

Table 5: *Vehicle capacity input [Iversen, 2013]*

Vehicle loading capacity	8000 kg
Avg. weight for one newspaper page	2.425 gm
Avg. number of pages in a newspaper	50

The resulting vehicle capacity is approximately 65000 newspapers per vehicle.

The distribution costs consist of two elements, a variable routing cost and a fixed vehicle cost. Since all vehicles in the fleet are equal, these costs are independent of which vehicle is being used. We have used either the route lengths from the pre-generation or the arc lengths from Google Maps in order to calculate the routing costs for the path-flow models and arc-flow model, respectively. Table 6 shows the additional data needed to find routing costs.

Table 6: *Routing cost input*

Diesel Price	14 NOK/l
Fuel consumption	30 l/100km
Ferry price	410 NOK

The fuel consumption is the average fuel consumption for trucks with loads ranging between 8 and 10 tonnes, while the diesel price is the average price in Norway in 2014. The ferry price is the ticket price for the Horten-Moss ferry for vehicles up to 12 meters long. The ferry is used if this is the fastest mode of transportation between two nodes. We have not included tolls from toll roads in the transportation costs.

The fixed vehicle cost consists of labor costs for the driver and the cost of owning or hiring a vehicle. We assume that costs of hiring and owning a vehicle are similar and calculate the annualized cost of buying a vehicle today. The formula for annualized payments is shown in the equation below, where PV is Present Value, r is discount rate and n is the number of periods we make payments.

$$\frac{PV}{\frac{1-(1+r)^{-n}}{r}}$$

We assume the price for a new vehicle (PV) of the type our fleet consists of, to be 600000 NOK [Bertel O. Steen, 2014], the discount rate to be 5% and the number of payment periods (assumed same as useful life of a vehicle) to be 8 years. This results in annual payments of approximately 93000 NOK, i.e. 255 NOK per day.

We add labor costs and assume an average length of 3 hours per route and wages of 300 NOK per hour, hence the average labor costs associated with using one vehicle for one route is 900 NOK. In total the cost of using a vehicle once is therefore assumed to be 1155 NOK. In the path-flow model this fixed cost is added to every route cost.

9 Technical Analysis

In this section we test various technical aspects of the path-flow models with the aim of reducing solution times and improving the integer solutions. To reduce the solution time of the path-flow models various column generation procedures are tested. With the aim of improving the integer solutions found by performing general B&B, two fixing strategies that allow column generation to be applied after the root node is solved are tested. In Section 9.4 a comparison of the performance of the arc-flow model and the two path-flow models is presented. First we briefly explain some of the aspects concerning the implementation of the models.

9.1 Implementation

The models are written in the algebraic modelling language Mosel, implemented in Xpress-IVE and solved by Xpress Optimizer version 24.01.04. Xpress uses the Simplex method to solve linear programs and Branch and Bound to solve mixed integer programs (MIP) [Fair Isaac Corporation, 2009]. Xpress also has a built in presolver that tightens the problem by removing redundant constraints and variables, adding valid inequalities, etc. before solving the B&B.

As mentioned in Chapter 7 input data for the pre-generation of routes are found using Google Maps, and the data are extracted using a Python script. The pre-generation algorithm is written in C++ and implemented in Visual Studio 2010. Other input data to Xpress besides the routes has been calculated and sorted in Excel, but is handled directly in datafiles in Mosel. All the mosel files, C++ code and input data files can be found as attachments in DAIM.

The computer used is specified in Table 7.

Operating system	Microsoft Windows 7 Enterprise 2009
Processor	Intel(R) Core(TM) i7-3770 CPU 3.40 GHz
Memory (RAM)	16 GB

Table 7: *Computer specifications*

The arc-flow model is solved in Xpress as a MIP. First the presolve is executed, then the LP relaxation of the model is solved, before the MIP is solved by the B&B algorithm. For the path-flow models the RMP is solved as an LP in order to communicate the correct dual information to the subproblems. To obtain the correct dual variable values the presolver must be turned off for solving the RMP. The SPs are solved as MIPs and the solution process is the same as for the arc-flow model. When the RMP is solved the basis is saved so that in the next iteration the RMP can be solved starting from the previous basis. This will reduce the solution time of the RMP. When no more columns with negative reduced costs are found in the SPs, the RMP is also solved by B&B.

In Xpress-IVE all dynamic arrays are created empty and thus dynamic variables must be created explicitly [Fair Isaac Corporation, 2009]. If an index in a dynamic array is empty no extra memory or processing power is used in handling the array. According to Baricelli et al. [1998] this feature can be used to exclude all variables from the model which we know will be zero in the solution. We have taken advantage of this by not creating the variables that will not be needed. For instance, in the arc-flow model an arc variable w_{ijk} could be defined for all arcs between nodes, but since we do not allow vehicles to visit more than one facility the arcs between facilities are not created. For both the arc-flow and the path-flow models the production and loading variables for time slots before the newsroom deadline and after the latest delivery deadline are not created either. In the VR-SP the delivery variables are only created for customers and products where there is a demand. Operations over index sets will only include the indices of variables that have been created and therefore creating only the necessary variables can reduce solution times significantly.

The RMP needs to start with an initial set of feasible columns to find feasible dual values in the first iteration. Especially for D2SP, generating a feasible set of schedules and delivery patterns can be hard. An alternative is to add slack variables to some of the constraints so it is possible to start without any initial columns. We have added slack variables s_{ip} to constraints (6.28) in the RMP, which makes sure all demand is delivered. With slack variables added to these constraints it is feasible to neither produce nor deliver any products. The slack variables are also added to the objective function with high costs so they will quickly disappear from the basis and not be a part of the solution.

$$\alpha_{ip}| \qquad \sum_{k\in K}\sum_{r\in R}\sum_{w\in W} Y_{ipkrw}\lambda_{krw} + s_{ip} \geq 1 \qquad i \in I^C, p \in P | D_{ip} > 0 \tag{9.1}$$

Preliminary testing of the path-flow model with two subproblems identified that when a schedule is chosen in the IP solution, constraints (6.29) and (6.30) in the RMP force all vehicles that are loaded in that schedule to use a route even though it might not be necessary. To allow production schedules to be used without forcing all vehicles to leave, dummy routes that do not visit any customers have been added to each facility. Any given vehicle can use both a dummy route and one real route, but these must leave from different facilities, i.e. a vehicle can only use one route from each facility. There is a cost associated with the dummy routes to make sure that these only are used when necessary. The cost consists of the cost of using a vehicle, but no transportation costs. If dummy variables are used in the solution the cost is subtracted from the objective value to find the true costs.

All technical testing in the following section will be tested on the smaller instance (N1) with the possibility of cooperation between Amedia and Schibsted, i.e. all products can be printed inn all facilities.

9.2 Decomposition with two subproblems

In this section technical aspects of the D2SP model are tested. Starting with testing different column generation procedures, followed by testing two fixing strategies that apply column generation after the root node.

9.2.1 Column generation strategy

When generating columns there are several different approaches as to how to add columns to the RMP. In this section we test different approaches to generating and adding columns to the RMP for D2SP, with the aim of reducing the solution time of the LP relaxation.

One approach is to solve the SPs to optimality in every iteration and add the column with minimal negative reduced cost, contrarily only the first column with negative reduced cost can be added. The latter may be particularly effective if the SP is computationally demanding to solve. This is because it may not be necessary to find the exact optimal solution, as any solution with a negative reduced cost can potentially be an entering variable in the basis and lead to a better solution. This approach will be more effective in the the beginning when all columns with negative reduced cost are expected to notably improve the solution to the RMP.

On the other hand, by adding non-optimal columns, the RMP may need more columns to find the optimal solution, i.e. more iterations will be needed. There will be a trade-off between the number of iterations and the computational effort needed to solve the SP. According to Vanderbeck and Savelsbergh [2006] the most efficient procedure will depend on the structure of the problem.

In the D2SP model the PAS-SP can take a while to solve, but is only solved once for each facility, while the VR-SP is computationally efficient to solve for each combination of routes and vehicles, but has to be solved for many combinations. It is therefore reasonable to assume that different approaches will be advantageous for the column generation in the VR-SP and PAS-SP. Although solving the MIP for the PAS-SP to optimality can take a long time, a relatively small gap (under 3%) is usually found within 60 seconds. We therefore choose to stop the B&B search in the PAS-SP after 60 seconds (an alternative would be to stop after reaching a certain gap) in order to reduce the total time and computational effort of solving the root node. If no negative reduced costs are found within 60 seconds, the algorithm would stop if the VR-SP does not generate any new columns either. However, in our case 60 seconds has always proven to be enough to find new columns in the PAS-SP, e.g. the problem is always solved to optimality in the last iteration. As mentioned, the VR-SP on the other hand is computationally efficient to solve to optimality for each vehicle and route, but there are many combinations of these and thus many SPs to solve. In the first iterations many columns with negative reduced cost will be found, even though these might not be good delivery patterns. The reason for this is that all the dual variables have very high values to begin with, but the patterns generated may not be favourable after a few iterations. To limit this effect, it could therefore be advantageous to add fewer columns in the first iterations. Therefore, we explore the options of not adding all columns with negative reduced cost from

Table 8: K,R ordering

Vehicle	Route
1	1
1	2
1	3
1	4
1	5
2	1
2	2
2	3
2	4
2	5
3	1
...	...

Table 9: R,K ordering

Vehicle	Route
1	1
2	1
3	1
1	2
2	2
3	2
1	3
2	3
3	3
1	4
2	4
...	...

Table 10: Mix ordering

Vehicle	Route
1	1
2	2
3	3
1	4
2	5
3	1
1	2
2	3
3	4
1	5
2	1
...	...

the VR-SP in each iteration, to see if this will reduce the solution time for the root node.

In addition, we test different ways of going through the combinations of vehicles and routes when solving the VR-SP. The pre-generated routes are ordered by facility and by the number of customers in each route, but when solving the VR-SPs there may be other ways of ordering that lead to lower solution times. In addition, our test case has a homogeneous fleet, so the reduced costs for a given route will be identical for all vehicles in the first iterations and it may not be necessary to generate columns for all vehicles and all routes to start with. Therefore, ordering the vehicles and routes in different ways may also affect the solution time.

We have tested going through all of the routes per vehicle (K,R), all of the vehicles per route (R,K), mixing these two, as well as randomizing the order. Mixing the (K,R) and (R,K) approaches is essentially going through all of the vehicles and all of the routes simultaneously. The different ways of ordering the combinations of vehicles and routes for an example with 3 vehicles and 5 routes are demonstrated in Table 8-10. The different ways of ordering routes and vehicles are often referred to as "orderings" throughout the rest of the thesis.

The different ways of ordering vehicles and routes have been tested for different numbers of columns added from the VR-SP per iteration. The test case N1 includes 130 routes and 7 vehicles which results in 910 different combinations of vehicles and routes. "Columns added per iteration" refers to the maximum number of columns added from the VR-SP. For 910 columns per iteration this basically means to solve the VR-SP for all combinations of vehicles and routes. In the cases where fewer columns are added per iteration, as soon as the maximum number of columns have been found the RMP is resolved. In the next iteration the VR-SP resumes in the same place it stopped. E.g. for K,R ordering, if the last iteration stopped after solving for vehicle 4, route 16 it would start solving for vehicle 4, route 17 in the following iteration. If the maximum number of columns is not found the VR-SP is solved for all 910 combinations. In the last iterations few columns with negative reduced cost will be found so almost all 910 combinations will have to be solved. For the PAS-SP, the columns with most negative reduced costs are added for each facility in each iteration. Table 11 summarizes the results from these tests. The objective value for the LP relaxation of N1 using D2SP is 26494.8. The best solution time for each of the orderings is written in bold.

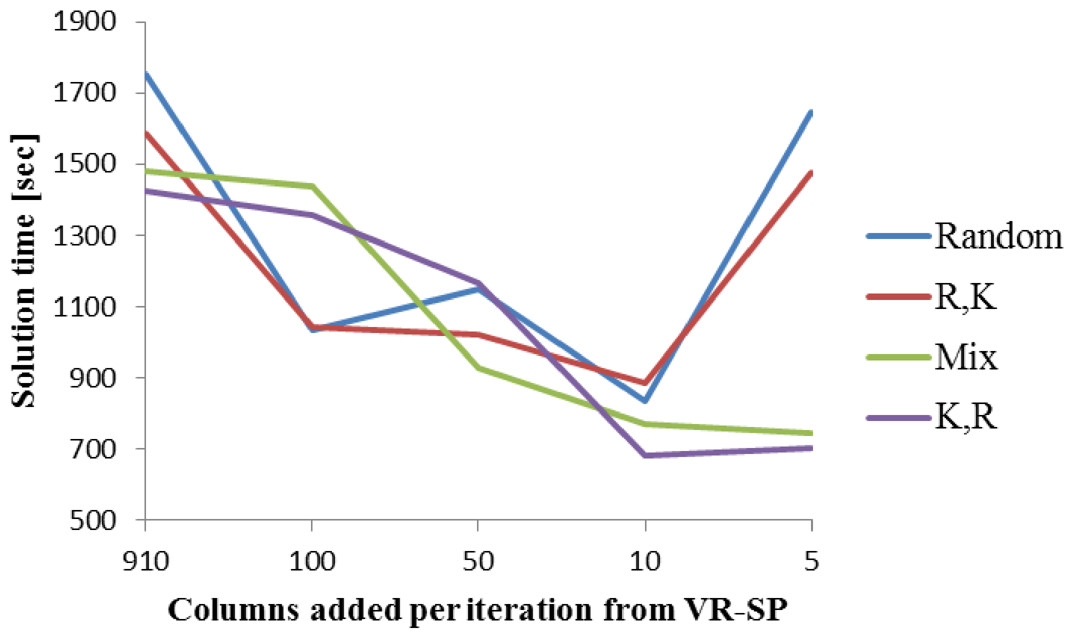
Table 11: *Results from testing column generation procedures for D2SP*

	Columns added per iteration	**910**	**100**	**50**	**10**	**5**
K,R	Time to solve LP (sec)	1423	1355	1165	**680**	701
	Number of iterations	47	59	68	119	161
	Number of patterns generated	5203	2572	2118	1169	798
	Number of schedules generated	89	114	127	220	280
R,K	Time to solve LP (sec)	1587	1041	1021	**884**	1475
	Number of iterations	47	49	57	99	155
	Number of patterns generated	5213	2322	1907	977	770
	Number of schedules generated	90	89	104	160	227
Mix	Time to solve LP (sec)	1481	1437	929	772	**744**
	Number of iterations	43	55	51	87	125
	Number of patterns generated	5202	2013	1588	860	617
	Number of schedules generated	84	100	97	166	227
Random	Time to solve LP (sec)	1754	1034	1150	**836**	1645
	Number of iterations	48	49	57	83	142
	Number of patterns generated	5081	2209	1673	807	704
	Number of schedules generated	87	94	108	160	273

It is clear that when the number of columns added per iteration is reduced, the number of iterations increases for all of the orderings. This is due to the fact that more iterations are needed to find the optimal solution when fewer columns are added per iteration. The total number of delivery patterns added to the RMP decreases in line with the decrease in columns added per iteration, meaning that better patterns are found, and less unnecessary variables are added to the RMP, which in turn will reduce the solution time of the RMP. As the number of iterations increases so does the number of production schedules created.

As mentioned earlier in the section, there is a trade-off between the time it takes to solve each iteration and the total number of iterations solved. Figure 13 illustrates how the solution time changes when the number of columns added per iteration is decreased for each of the different orderings. With the exception of Mix ordering, all of the orderings are solved fastest when adding 10 delivery patterns per iteration. For Mix ordering, adding 5 patterns per iteration leads to the lowest solution time. It seems that a good balance between the number of delivery patterns added and iterations (and thereby production schedules added) is found when 10 VR-SP columns are added per iteration which gives approximately 5 delivery patterns per schedule. All of these procedures result in reductions in solution time by more than 40%. The best solution time of all is found when using K,R ordering and 10 columns

Figure 13: *Solution times for LP for different column generation procedures for D2SP*



added per iteration. The root node is solved to optimality after 680 seconds, which is a 52% reduction from the procedure that goes through all 910 combinations in every iteration. Table 12 presents the change in solution time between going through all combinations in each iteration and the best procedure found for each ordering.

Table 12: *Reduction in solution time for each ordering, compared to adding all columns*

Best procedure for each ordering	K,R 10	R,K 10	Mix 5	Random 10
Change in solution time	-52 %	-44 %	-48 %	-52 %

Through studying the output from running the various procedures it can be seen that the number of delivery patterns with negative reduced cost in each iteration decreases rapidly. In the last iterations few or no new columns are found when solving the VR-SP and going through all combinations of routes and vehicles in every iteration prolongs the solution time. An alternative would be to solve several PAS-SPs successively as soon as the number of new columns from the VR-SP has decreased to a certain level, and after that only solve the VR-SP e.g. every fifth iteration.

In conclusion, adding less than all columns from the VR-SP considerably reduces the solution time of the root node. It is important to find a good balance between the number of columns added per iteration and the total number of iterations. For D2SP this also means finding a balance between patterns created and schedules created. The ordering of vehicles and routes does not affect the solution time significantly. For the best column generation procedures the solution time is more than halved.

Integer solutions to the D2SP

When solving the LP relaxation the aim of testing different column generation procedures is to reduce the solution time. When solving the IP, however, it may be advantageous to have generated more columns because the same columns that are optimal for the LP relaxation may not be optimal, or even feasible, when solving the IP. When solving D2SP as an IP using the built in B&B in Xpress none of the column generation procedures lead to feasible integer solutions, i.e. the slack variables in constraints (9.1) have to be used. Even though optimal delivery patterns have been generated, sufficient production schedules are not found. The IP objective functions vary depending on which of the procedures have been used, but at least three slack variables are used in all of the cases. In the following sections we investigate alternative approaches to improve the IP solutions.

9.2.2 Fixing strategies

As discussed in Section 6.1, when going from the solution of the LP relaxation to an IP solution by general B&B, optimal or even feasible solutions cannot be guaranteed. We see an example of the latter in D2SP where the scheduling columns generated for the LP relaxation are insufficient to find a feasible integer solution without the use of slack variables. In order to find a feasible integer solution additional columns are needed. As mentioned in Section 6.1 one option is to allow column generation in every node in the B&B tree, i.e. Branch and Price. Implementing a full Branch and Price algorithm is out of the scope for this thesis, but we investigate other alternative solution approaches that generate additional columns after solving the root node. An algorithm that generates new columns after successively fixing vehicles to either facilities or routes is implemented. The approach can be compared with a "depth first" branching strategy. The two alternative approaches will be described and tested for D2SP in the following sections.

Fixing vehicles to facilities

The first fixing strategy consists of successively fixing vehicles to facilities, according to where the routes with the highest fractional value in the root node originates. The RMP and SPs are then resolved with all routes leaving from other facilities removed for the fixed vehicle. This is repeated for a predetermined number of fixations. The algorithm is explained below.

Algorithm for fixing vehicles to facilities:

- Solve the root node
- For all vehicles that have not already been fixed search through the route variables λ_{krw} to find the one with the highest fractional value.
- Fix vehicle k to leave from the facility where the route with highest fractional value originates.
  -Delete all delivery variables for this vehicle that leave from other facilities.
  -Delete all production schedules for this vehicle in other facilities.
- Resolve the RMP to find new dual values

- Resolve the VR-SP
  -For vehicle k and routes originating in the fixed facility
  -For all other vehicles and combinations of routes.
  -Add new delivery patterns to the RMP
- Resolve the PAS-SP
  -For the facility where vehicle k has been fixed
  -For the other facility remove k from the subproblem
  -Add new columns
- Resolve RMP
- Continue until all or a predetermined number of vehicles have been fixed to a facility.

The fixing strategy algorithm is implemented in D2SP and tested using the column generation procedures that generate the highest number of delivery patterns and the highest number of schedules (all orderings that add 910 and 5 columns per iteration, respectively). The approach improves the solutions in that fewer slack variables are used, but it does not provide feasible solutions without the use of slack variables. The main problem is that insufficient production schedules are created to cover all the demand when the IP is solved. Even though optimal delivery patterns are generated, the corresponding schedules are not found.

In every fixation many delivery patterns are deleted for the fixed vehicle, so when resolving the VR-SP there are many negative reduced costs associated with this vehicle. New schedules are also created after each fixation, but the PAS-SP stops finding new schedules long before the VR-SP stops finding new delivery patterns. The only costs associated with the production schedules are the plate costs, and as a result there will be very many degenerate solutions to the PAS-SP with equal costs. However, once schedules that cover demand in the LP relaxation of the RMP are generated, there is little incentive to generate additional schedules.

In the LP relaxation of the RMP, fractions of schedules can be used so demand is easily covered by a combination of schedules. When the IP is solved, however, only one schedule can be chosen for each facility. This requires the existence of either one single schedule, or a pair if two facilities are used, that covers all demand and loads the correct vehicles with respect to the delivery patterns generated. The use of dummy routes solves the problem where schedules load vehicles that do not depart, but making sure the right quantity of the right products are loaded to the right vehicles is more difficult. There may e.g. exist a schedule where all of the demand is produced and loaded to the right amount of vehicles, but if the right products are not loaded to the exact vehicle that is assigned to deliver said products in the delivery patterns, the solution will not be feasible.

An alternative solution approach is to combine fixing vehicles to facilities with generating a larger pool of columns when the column generation is applied to the PAS-SP. However, this approach does not result in feasible solutions for D2SP either.

Fixing vehicles to facilities and reapplying column generation does not provide sufficient signals to the PAS-SP to generate schedules which are feasible with integer requirements. To improve the communication between the PAS-SP and VR-SP information about which vehicles that can deliver which products is needed. However, for this to be beneficial it is important to do so without restricting the solutions too much. In the following section we investigate an approach that fixes vehicles to routes, which may contribute to the communication of which products to load in which vehicles.

Fixing vehicles to routes

In this section we will apply a more restricting fixing strategy with the aim of providing better communication between the PAS-SP and VR-SP.

The algorithm for fixing vehicles to routes is similar to fixing vehicles to facilities, but now the vehicle is also fixed to the route with the highest fractional value. Delivery patterns not including this route are removed from the problem for the fixed vehicle, and the VR-SP for this vehicle is only resolved for the fixed route. The VR-SP is solved for all routes for all the remaining unfixed vehicles. In the PAS-SP the vehicle is removed for the facility that the fixed route does not leave from. Some additional constraints are added to the PAS-SP for the facility that the fixed route does leave from:

Sets and Parameters

K_i^{FIX}	The set of fixed vehicles in facility i
I_{kr}^{FIX}	Set of customers that is on route r that vehicle k is fixed to
D_k^{MIN}	The smallest demand of any product on the fixed route for vehicle k

$$\sum_{t \in T} q_{ipkt} \leq \sum_{i \in I_{kr}^{FIX}} D_{ip} \qquad p \in P, k \in K_i^{FIX} \tag{9.2}$$

$$\sum_{p \in P} \sum_{t \in T} q_{ipkt} \geq D_k^{MIN} \qquad k \in K_i^{FIX} \tag{9.3}$$

$$t_k^F \leq T_{kR}^S \qquad k \in K_i^{FIX} \tag{9.4}$$

Constraints (9.2) and (9.3) make sure that fixed vehicles can at most be loaded with the total demand of all products on the route they are fixed to and must at least be loaded with the minimum demand. This will improve the schedules created with respect to loading products to the same vehicles that deliver the products. Fixed vehicles must also be finished loading before the latest start time for the route they are fixed to, this is handled by (9.4). Capital R represents the fixed route of vehicle k. In addition, existing schedules that load the fixed vehicle after the latest start time for the fixed route are removed.

Fixing vehicles to routes is a more restrictive branching strategy than fixing to facilities. Note however, that vehicles are not locked to using the routes they have been fixed to by restrictions, but all other route options have been removed. When there are more vehicles available than needed this provides the alternative of not using that vehicle if other routes prove to be better after fixing. An alternative, more restrictive, branching strategy would be to add a constraint in the RMP that requires the fixed vehicle to use that route.

As mentioned in the previous section, an alternative solution approach is to combine fixing vehicles to routes with generating a larger pool of columns when the column generation is applied to the PAS-SP. This strategy leads to the best results and will be presented here.

The fixing strategies have been tested for all of the column generation procedures that add 910 and 5 columns per iteration. All the seven vehicles have been successively fixed to routes, with column generation applied until LP optimality in between each fixation. The IP has been solved after every fixation to enable an analysis of which fixation level is appropriate. Feasible solutions without slack variables were found for all of the procedures that go through 910 VR-SPs per iteration with the exception of random ordering. Fixing vehicles to routes improved the solutions for the other column generation procedures as well, although feasible solutions were not found, the number of slack variables were reduced in every case. Results from the tests that led to feasible solutions without slack variables are summarized in Table 13.

The number of fixations needed to reach a feasible solution varies depending on which column generation procedure is used. However, all of the feasible solutions are found after fixing at least 4 vehicles to routes and none are found for fixing all vehicles.

Table 13: *Solutions found when fixing vehicles to routes in D2SP*

Column generation procedure	**K,R 910**	**R,K 910**	**Mix 910**
Number of feasible solutions found	Three	One	One
Best solution found after fixing number	6	5	5
Best solution objective value	47078	49947	45294

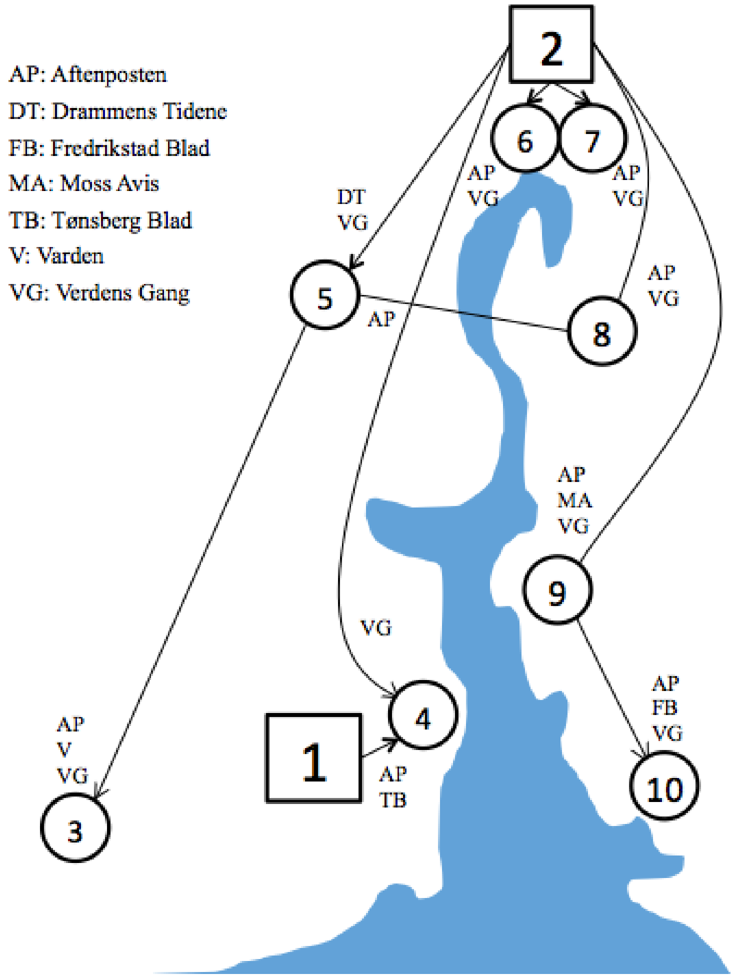
K,R ordering with 910 columns added per iteration leads to three feasible solutions after 4, 5 and 6 fixations. The most promising solution is found after five fixations using the Mix 910 column generation procedure. Table 14 summarizes the fixation process for the Mix 910 case, presenting which routes the vehicles have been fixed to in each fixation and the IP solution after five vehicles are fixed. For the first four fixations sufficient production schedules have not been generated to provide feasible solutions.

Table 14: *Fixations resulting in the best integer solution for D2SP*

	Facility	**Customers in route**
1st fixing	2	7
2nd fixing	2	6
3rd fixing	2	8, 5, 3
4th fixing	1	4
5th fixing	2	9, 10
Unfixed vehicle	2	5
Unfixed vehicle	2	4
IP Objective Value		45294

The routing and delivery patterns are presented in Figure 14. The arrows indicate the last customer in a route and the return to the facilities is not included in the figure.

Figure 14: *Routing solution for 5 fixations (Mix 910)*

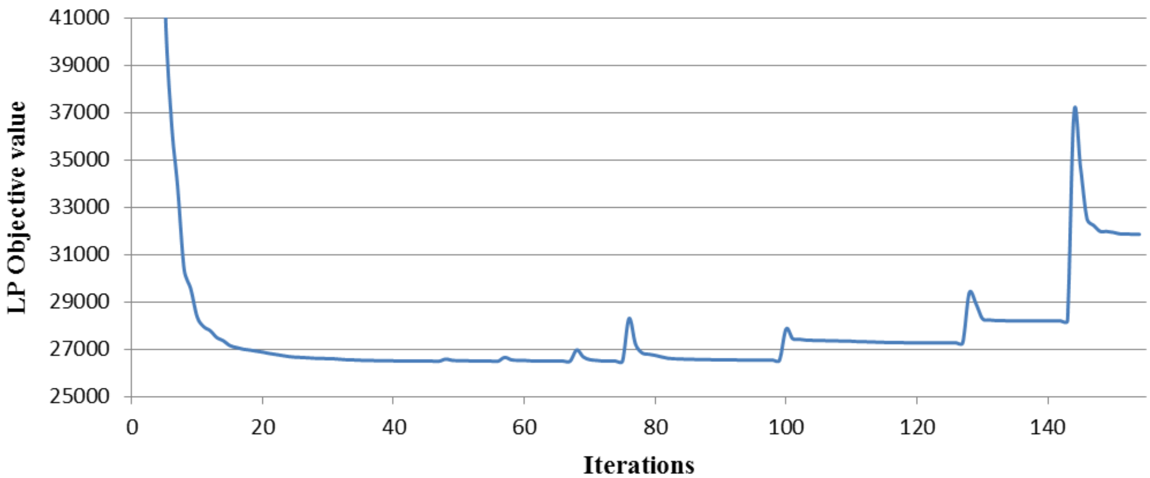


The first three vehicles are fixed to routes that leave from Facility 2 which is Nydalen, while the 4th is fixed to a route leaving from Facility 1 which is Stokke. In the 5th fixation a vehicle is fixed to visit customers 9 and 10 (Fredrikstad and Moss) from Nydalen. After column generation and resolving the IP a feasible solution is found with an objective value of 45294. The two last vehicles remain unfixed and visits customers 5 (Drammen) and 4 (Tønsberg) from Nydalen in this integer solution. Two dummy routes have been used, and the cost of these has been subtracted from the objective value.

For 6 fixations (not presented in the table), the route with the highest fractional value originates from Nydalen and includes customers 8, 9 and 5 (Ski, Drammen and Porsgrunn). Fixing a vehicle to use this route leads to an infeasible solution where the slack variable s_{47} is used, i.e. product 7 (VG) is not delivered to customer 4 (Tønsberg). In this case fixing the 6th vehicle is too restrictive. When applying fixing strategies it is important to find a balance between being restrictive enough to generate new appropriate columns and being too restrictive by cutting away good or optimal solutions to the problem.

By looking at the change in the LP objective value after every fixation we can see that every fixation restricts the LP relaxation. The changes in the LP value after each iteration can be seen in Figure 15.

Figure 15: *LP bound after fixations*



The objective value decreases until the LP relaxation has been optimized. After every fixation the LP objective value increases since the problem has been restricted. The fixations can be seen clearly in Figure 15 where the graph jumps up to higher objective values. When additional columns are generated the LP objective value is improved until the new restricted problem has been solved to optimality. After the first fixation the original LP bound is found, but after the fourth fixation the LP bound after column generation has increased. This bound is further increased after the 5th, 6th and 7th fixations. It is evident that after fixing a certain number of vehicles the fixing may be too restrictive and worsen the solution. This may also be the case for the IP solution. This can be seen in all of the cases presented in Table 13 after seven vehicles are fixed. As explained above, when six vehicles are fixed using the Mix 910 procedure no feasible solution is found. Another example can be seen using procedure RK 910 where three feasible solutions are found. The first solution is found after the 4th fixation and two improved solutions after the 5th and 6th fixations, however, when 7 vehicles are fixed no feasible solution is found. Fixing too many vehicles ultimately leads to an infeasible solution.

In conclusion, fixing vehicles to routes greatly improves the IP solution compared with solving D2SP with only general B&B. Regardless of which column generation procedure is used the solution is improved and for three of the procedures feasible solutions are found. Although the best solution is not optimal, we have found a pessimistic bound through applying a fixing strategy that allows for column generation after the root node. We know the solutions is not optimal since the arc-flow model has found the optimal solution to this instance (N1).

9.3 Decomposition with one subproblem

In this section technical aspects of the D1SP model are tested. Firstly, column generation procedures are tested with the aim of identifying procedures that can reduce the solution time. In Section 9.3.2 the fixing strategies presented in the previous section are applied to D1SP.

9.3.1 Column generation strategy

In this section we test the same column generation procedures as in section 9.2.1 for D1SP. Tables 15 and 17 summarize the results. The objective value for the LP relaxation of N1 using D1SP is 11696.9.

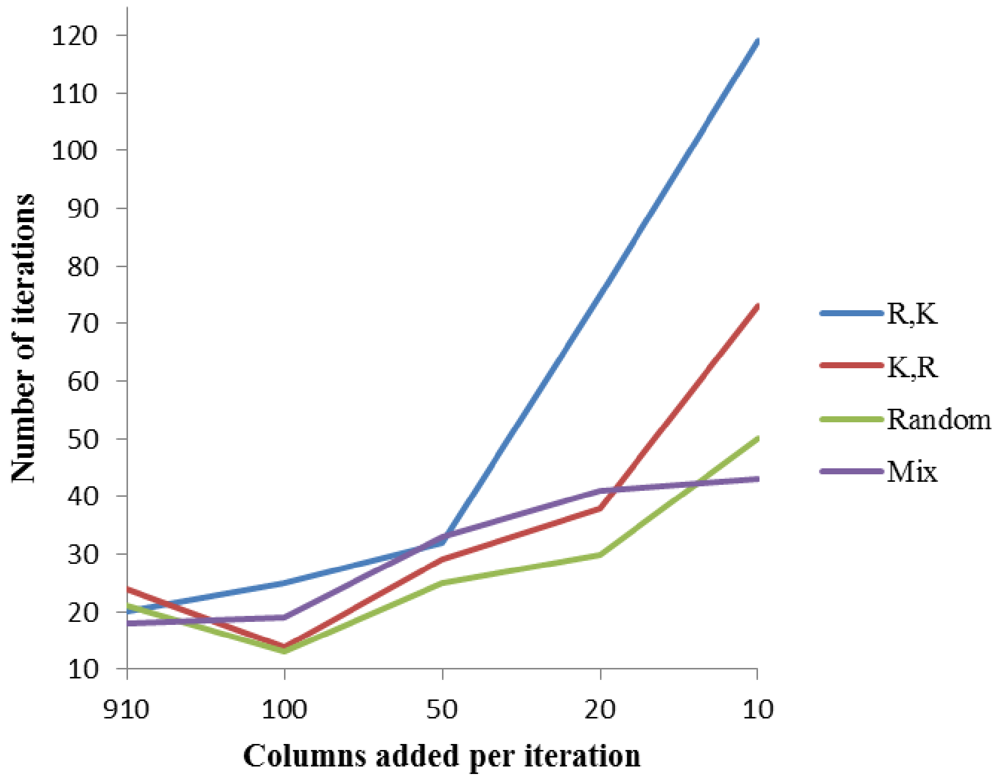
In the same way as for D2SP, we see that as the number of columns added per iteration is decreased the number of iterations needed to reach optimality increases, and the number of patterns added to the RMP decreases. This is due to the fact that when less columns are added per iteration better columns are found and less columns are needed in total, but it takes more iterations to find these. As explained in section 9.2.1, there is a trade-off between the time it takes to solve each iteration and the total number of iterations.

Table 15: Results from testing column generation procedures for D1SP

	Columns added per iteration	**910**	**100**	**50**	**10**
K, R	Time to solve LP (sec)	449	**105**	235	327
	Number of iterations	24	14	29	73
	Number of patterns generated	3399	1006	1061	685
R, K	Time to find optimal LP	363	236	**130**	376
	Number of iterations	20	25	32	119
	Number of patterns generated	3485	1800	1456	1155
Mix	Time to find optimal LP	305	240	226	**111**
	Number of iterations	18	19	33	43
	Number of patterns generated	3890	960	584	418
Random	Time to find optimal LP	343	**116**	282	177
	Number of iterations	21	13	25	50
	Number of patterns generated	3561	894	889	479

We see this effect for K,R and R,K in that the solution times are relatively high when all columns with negative reduced cost are added. Solution times are reduced when 100 and 50 columns are added per iteration, but increase again when only 10 columns are added due to the fact that the number of iterations has increased significantly. Figure 16 illustrates how the number of iterations changes when the number of columns added per iterations is decreased for each of the different ways of ordering vehicles and routes.

Figure 16: *Number of iterations to solve the LP relaxation for different column generation procedures*



For mix and random ordering the number of iterations does not increase as much when the number of columns added is decreased to 10, so the trade-off between the time to solve each iteration and the time it takes to solve additional iterations is not as predominant. For mix ordering, adding 10 patterns gives the shortest solution time and also generates the least columns of all the tested procedures. In other words, better columns are found faster. This way of ordering is the fastest way of covering all route and vehicle numbers, and fewer columns can therefore be added per iteration. For K,R and R,K more iterations have to be solved to cover the last vehicle and last route, respectively.

The best solution overall is found using K,R ordering and adding 100 columns per iteration. Compared with going through all VR-SPs in every iteration the solution time is reduced by 77%. The difference in solution time between the best solution found for each ordering and going through all combinations in each iteration can be found in Table 16.

Table 16: Reduction in solution time for each ordering, compared to adding all columns

Best procedure for each ordering	**K,R 100**	**R,K 50**	**Mix 10**	**Random 100**
Change in solution time	-77 %	-64 %	-46 %	-66 %

As discussed in Section 9.2.1, in the first iterations many columns with negative reduced cost will be found even though many of these might be poor solutions. Adding fewer columns per iteration in the beginning can therefore reduce the solution time. The problem with adding very few columns per iteration is that the number of iterations increases, as we see in the case where 10 columns are added for K,R and R,K.

To see if the number of iterations, and thus solution time can be reduced in these cases we test a procedure that adds 10 columns in the first iterations and incrementally adds more and more columns per iteration. When ten iterations have been carried out 100 columns are added for the rest of the iterations. (The number is restricted to 100 in order to avoid solving too many iterations without finding the required amount of columns with negative reduced cost towards the end.)

Table 17: Incrementally adding more columns per iteration

	Columns added per iteration	**10 —>100**	**10**
K,R	Time to find optimal LP	166	326.66
	Change	-49 %	-
	Number of iterations	22	73
	Number of patterns generated	1175	685
R,K	Time to find optimal LP	272	375.89
	Change	-28 %	-
	Number of iterations	34	119
	Number of patterns generated	2117	1155

Compared with the case where 10 columns are added per iteration the number of iterations and solution times are considerably reduced for both tests. However, for K,R ordering, adding 100 for each iteration is still the best strategy with respect to solution time. For R,K ordering, adding 50 is still superior.

In conclusion, which strategy leads to the shortest solution time depends both on the number of columns added to the RMP in each iteration and in which order the VR-SP is solved for combinations of vehicles and routes. The best strategy overall with respect to solution time is found when going through all routes per vehicle (K, R) and adding 100 columns per iteration. This leads to a reduction in solution time of 77 % compared with adding all columns with negative reduced cost in each iteration.

Comparison of column generation procedures for D2SP and D1SP

When comparing results from this section with the results for D2SP (Section 9.2.1) we see that which procedure is best indeed depends on the structure of the problem. For D2SP the best results are found when adding 10 or less columns per iteration for all orderings, while for D1SP the best results are more dependent on the ordering.

In addition, the column generation strategies are more effective for D1SP (reducing the solution time by 77% compared with 52% for D2SP). This is probably due to the fact that for D2SP the PAS-SP affects the number of iterations, and hence solution time, and the procedures we have tested affect only the column generation in the VR-SP.

We also see that solution times for the LP relaxation in D1SP are substantially shorter than for D2SP. This is partly due to the fact that for D2SP the PAS-SP is a MIP which requires more computational effort to solve than in D1SP where the PAS constraints are in the RMP which is solved as an LP. In addition, more iterations are needed to reach optimality for D2SP. This is because the PAS and VR are in separate subproblems and coordinating them to find the optimal schedules and delivery patterns is harder than for D1SP which only has one subproblem.

Integer solutions to the D1SP

As discussed in section 9.2.1, the best column generation procedure for solving the root node may not be the best choice for solving the IP. Therefore the IP is solved using all of the procedures to see if there is a difference in the solutions.

All of the column generation procedures for D1SP lead to feasible integer solutions. However, some of the procedures that generate very few columns result in poorer solutions than the procedures that generate larger pools of columns. We present the objective values for the procedures that give the most promising results for the LP relaxation, in addition to K,R and R,K ordering with 910 columns added per iteration, because these procedures result in a large pool of generated columns.

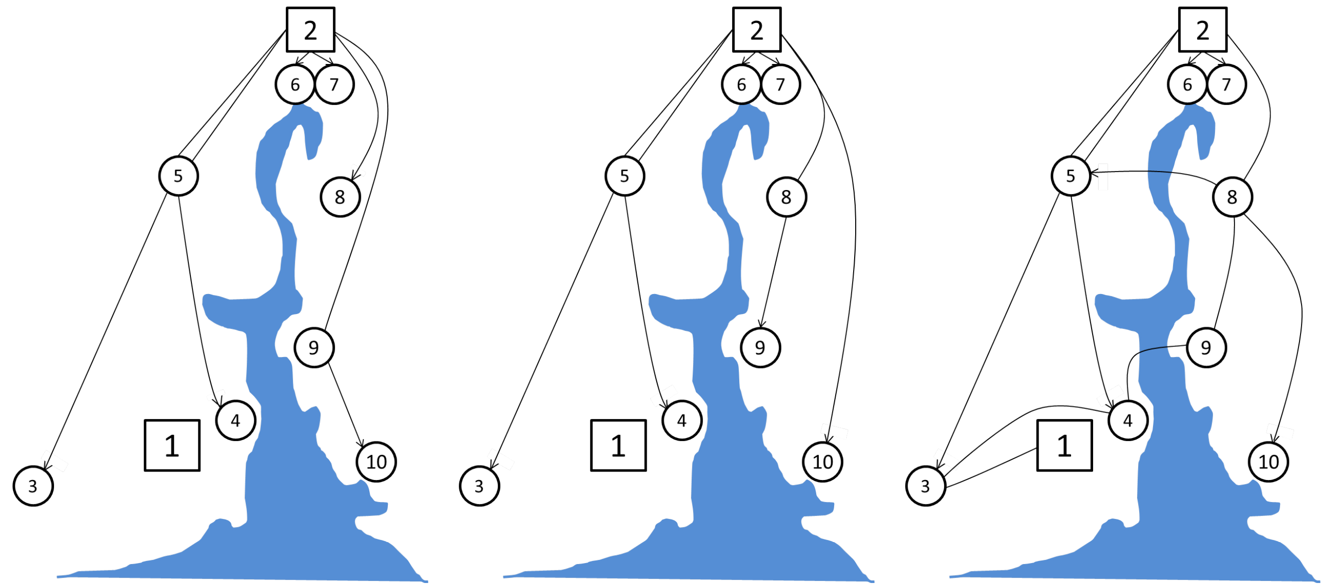
Table 18 presents the objective values when the IP is solved by B&B for each of the procedures. The tests have been run to a 0.01% relative gap or terminated after 3600 seconds runtime.

Table 18: *Solving the integer problem using different column generation procedures*

	K,R 910	**K,R 100**	**R,K 910**	**R,K 50**	**Mix 10**	**Random 100**
IP Objective value	38397	38397	38397	38677	38674	38397
Solution time [s]	3600	112	3600	3600	24	72

The best solution found by the D1SP gives an objective value of 38397 NOK. This solution is found using both of the procedures that solve 910 VR-SPs in every iteration, as well as K,R and Random ordering with 100 columns added per iteration. Figure 17 illustrates the different routing solutions.

The solution found using D1SP improves the upper pessimistic bound found with D2SP in section 9.2.2 by 15%. The arc-flow model has solved this N1 instance to optimality with an objective value of 37918 NOK, which is lower than the currently best integer solution found with D1SP. In the next section we therefore investigate if a fixing strategy can provide better integer solutions for this model.



(a) Objective value 38397 (b) **R,K 50 -** Objective value 38677 (c) **Mix 10 -** Objective value 38674

Figure 17: *Routing of integer solutions for N1 using D1SP*

9.3.2 Fixing strategies

In order to see if the solution found through B&B can be improved if more columns are generated after the root node is solved, we apply similar fixing strategies as those presented in section 9.2.2 to D1SP.

Fixing vehicles to facilities

This strategy is essentially the same as the one applied to D2SP with a few alterations due to the difference in decomposition. Since the PAS constraints are all included in the RMP it is easy to make sure that a fixed vehicle only is loaded in the facility it is fixed to. For the fixed vehicle, the production and loading variables in the RMP are only created for the fixed facility. For all unfixed vehicles all variables are created. The VR-SP is solved in the same way as for D2SP; for a fixed vehicle the SP is solved only for routes originating in the facility the vehicle is fixed to. Delivery patterns that are connected to other facilities are removed from the RMP.

The fixing strategies are tested using the four column generation procedures that provides the best IP solution with general B&B. All procedures are tested for fixing one to seven vehicles. All of the tests lead to the same IP solution as before the the fixing strategy is applied. For illustrative purposes Table 19 presents the fixation sequence when the number of fixations is set to 7 using K,R ordering and adding 100 columns per iteration. In the first fixation, the route that visits customer 7 (Eastern Oslo) from Facility 2 (Nydalen) has the highest fractional value, so the first vehicle is fixed to leave from this facility. In the second fixation a vehicle is fixed to Facility 2 due to the route visiting customer 5 (Drammen) and 8 (Ski) having the highest fractional value, and so on. The search for the highest fractional value is conducted only for routes that have not already led to fixing. After fixing the five first vehicles no other route variables have a non-zero value and thus the two last vehicles are not fixed to any facility. The 4th vehicle is fixed to Facility 1, but is not used in the IP solution, and the same solution is found as without the fixing strategy.

Table 19: *Fixing all vehicles to facilities for D1SP*

	Facility	**Customers in route**
1st fixing	2	7
2nd fixing	2	5,8
3rd fixing	2	6
4th fixing	1	3, 4
5th fixing	2	9, 10
6th fixing	-	-
7th fixing	-	-
Objective Value	38397	

Fixing a vehicle to leaving from a specific facility does not give sufficient incentive to generate delivery patterns that improve the integer solution. The fixations are not restrictive enough to lead to a significant change in the dual variables, so relatively few new columns are generated. Depending on which column strategy is used varying amounts of new delivery patterns are generated after every fixation, however, these have a relatively small negative reduced cost and the columns generated in the root node are still chosen in the integer solution.

In the next section fixing vehicles to routes is tested to investigate if this strategy will generate columns that improve the integer solution.

Fixing vehicles to routes

As before, the VR-SP for the fixed vehicle is solved only for the fixed route, and delivery patterns using other routes are removed from the RMP. Loading variables for the fixed vehicle are only created for the facility which it is fixed to. It is however not necessary to add constraints equivalent to (9.2)-(9.3) from section 9.2.2 to the RMP as constraints (9.5) and (9.6) take care of this.

$$\sum_{t \in T} q_{jpkt} - \sum_{i \in I^C} \sum_{r \in R_f} \sum_{w \in W} D_{ip} Y_{ipkrw} \lambda_{krw} \geq 0 \qquad j \in I^F, p \in P, k \in K \tag{9.5}$$

$$\sum_{r \in R_f} \sum_{w \in W} T^S_{kr} \lambda_{krw} - t_{ik} \geq 0 \qquad i \in I^F, k \in K \tag{9.6}$$

Fixing vehicles to routes is tested using the same column generation procedures as for fixing to facilities. All of the procedures result in the same solution for up to four fixed vehicles. After the 5th fixation, however, the IP objective values increase. Through adding too many restrictions some of the better solutions are removed from the pool of columns. To demonstrate this effect the fixation process for fixing all vehicles using K,R ordering and 100 columns added per iteration is presented in Table 20. The objective value for the integer solutions after every fixation are presented in the right column.

Table 20: *Fixing vehicles to routes for D1SP*

	Facility	**Customers in route**	**IP objective value**
1st fixing	2	6	38397
2nd fixing	2	7	38397
3rd fixing	2	10,9	38397
4th fixing	2	5,8	38397
5th fixing	1	3,4	**38647**
6th fixing	-	-	38647
7th fixing	-	-	38647
Solution:	2	6	
	2	7	
	2	10,9	
	2	5,8	
	2	5, 4	
	2	3	**38647**

As for fixing to facilities, only the first five vehicles are fixed to routes. The 5th vehicle is fixed to a route leaving from Facility 1 (Stokke) visiting customers 3 (Porsgrunn) and 4 (Tønsberg). However, if these routes were to be used in the integer solution either extra printing plates would have to be used in Facility 1 to fulfill all demand for customer 3 and 4, or a vehicle would have to drive from Facility 2 with some of the demand. Both of these options are more expensive than producing and distributing all demand from Facility 2, so in the IP solution the 5th vehicle is not used and two different routes leaving from Facility 2 are used instead. This results in an objective value of 38647 which is higher than the one found without fixing vehicles to routes. This leads to the conclusion that fixing routes to vehicles using D1SP is too restrictive when more than 4 vehicles are fixed.

The delivery patterns generated in the LP relaxation after fixing routes to vehicles are still not sufficient to find an improved integer solution. The reason this fixing solution is effective for D2SP is because by fixing vehicles to routes the coordination of the two subproblems is improved. For D1SP however, the PAS is included in the MP and so the coordination between the two subproblems is better and the fixing strategies do not improve the integer solution. To generate the complete columns to find the optimal IP solution a full Branch and Price algorithm could be implemented.

9.4 Comparison of models

In this section we compare the arc-flow, D2SP and D1SP models. We test the models on the two instances described in Section 8.1, N1 and N2. N1 is the smaller instance with 8 customers (of which 2 are locked) and N2 is the larger instance with 10 customers (2 locked). To reduce the solution time we have added an inequality that restricts the maximum number of customers visited by a vehicle. By adding equation 5.34 presented in Section 5.3 we say that a vehicle can maximum visit five customers. This is not a valid inequality here since it is possible to deliver one product to more than five customers with split delivery in both of the instances. At the same time a maximum of three customers is visited by any vehicle in the optimal solution to N1. We assume no more than five customers are visited by any vehicle in the optimal solution to N2. The main goal of this section is to compare the different models, and the same inequalities are applied to each of the models. The maximum number of customers visited by a vehicle is restricted with the above mentioned constraint in the arc-flow model. For D1SP and D2SP this is handled in the pre-generation of routes, making sure no route includes more than five customers.

The optimal fixing strategies and column generation procedures found in the previous sections are applied to D1SP and D2SP. For D2SP, this is to fix five vehicles to routes using a column generation procedure that goes through all vehicles and routes in every iteration. For D1SP K,R ordering is used and for N1 100 columns are added from the VR-SP per iteration. For the larger instance (N2) the column generation procedures are adjusted for the increased number of route-vehicle combinations. The number of combinations is approximately four times larger than for N1, so we add 400 columns per iteration.

Both models are run for ten hours, or until they close the MIP gap which is calculated like this in the Branch and Bound tree:

$$MIP\ gap = \frac{Best\ feasible\ solution - Best\ optimistic\ bound}{Best\ feasible\ solution} \tag{9.7}$$

First we evaluate the LP bounds provided by each model. The LP bound is the solution to the LP relaxation which is an optimistic bound to the problem with integer restrictions. D2SP and D1SP can only guarantee an optimal solution for the LP relaxation, but should provide a stronger LP bound than the the arc-flow model, due to the fact that the subproblems are solved with integer restrictions. Table 21 shows the different LP bounds provided by each model for both instances.

Table 21: *LP bounds provided by each model for both instances*

	N1	**N2**	**Rest to optimal IP solution for N1**
Arc-flow	10597.3	12469.9	100%
D1SP	11696.9	13791.7	96%
D2SP	26494.8	29544.6	42%
Optimal IP	37918	Not found	-

Both D1SP and D2SP do indeed provide better LP bounds than the arc-flow model, but the D2SP which has two subproblems solved with integer restrictions is superior. We can say that the arc-flow model has a 100 % gap to close in the B&B tree, which is the difference between the LP bound and the optimal IP solution. The right column shows how much of this gap remains to be closed with the improved LP bounds of D1SP and D2SP for instance N1. Optimal solution to N2 is not found, so we only look at the remaining gap for N1. D1SP reduces this to 96 %, but D2SP brings it down to 42 %. This is a good improvement over the arc-flow model, but there is still a considerable gap between the LP bound and the optimal solution. We look closer into this in Table 22 by breaking down the total costs to production costs and vehicle routing costs.

Table 22: *Cost breakdown for LP relaxations compared with optimal IP solution for N1*

	Production cost	**Routing cost**
Arc-flow	3041	7557
D1SP	3469	8228
D2SP	17350	9145
Optimal IP	28000	9918

The main reason why D2SP provides a better LP bound than the other models is the improvement in production cost, which is no surprise since the production part of the problem is solved with integer restrictions. However, the production cost is also the main reason why there still is a considerable gap to close in the B&B tree. When solving the LP relaxation small fractions of schedules can be used which leads to a low production cost. To improve this it could be interesting to add valid inequalities that improve the LP bound found by D2SP. Since every product has to use at least one set of printing plates, inequalities that ensure this should be investigated in future work.

We now investigate the different models' ability to find feasible solutions. The three models are tested on both instances, and we report the best solution found and corresponding bound after different runtimes. The results are illustrated in Figures 18 and 19.

For the smaller instance (N1) it is evident that the arc-flow model performs best. The optimal solution is found in less than two minutes, while neither of the path-flow models are able to find this solution. D2SP uses more than two hours to find a solution because five vehicles have to be fixed to routes, i.e. the problem with column generation is solved to LP optimality six times which is quite time consuming. The IP problem with five out of seven vehicles fixed to routes becomes trivial, and is solved in only four seconds. The column generation is also the reason why D1SP uses more time than the arc-flow model, and does not find the optimal solution.

For the larger instance (N2) the results are quite different. D1SP outperforms the arc-flow model. We cannot know if the solution found by D1SP is optimal since it is above the optimistic bound provided by the arc-flow model, but it is still preferred over the worse arc-flow solution. D1SP closes its own MIP gap, but the arc-flow model terminates after ten hours with a 6 % gap. Even though D1SP reaches a small gap within reasonable time, it experiences slow convergence towards closing the gap entirely. The MIP gap is 1% after about

Figure 18: *Objective value and bound after different runtimes for N1*

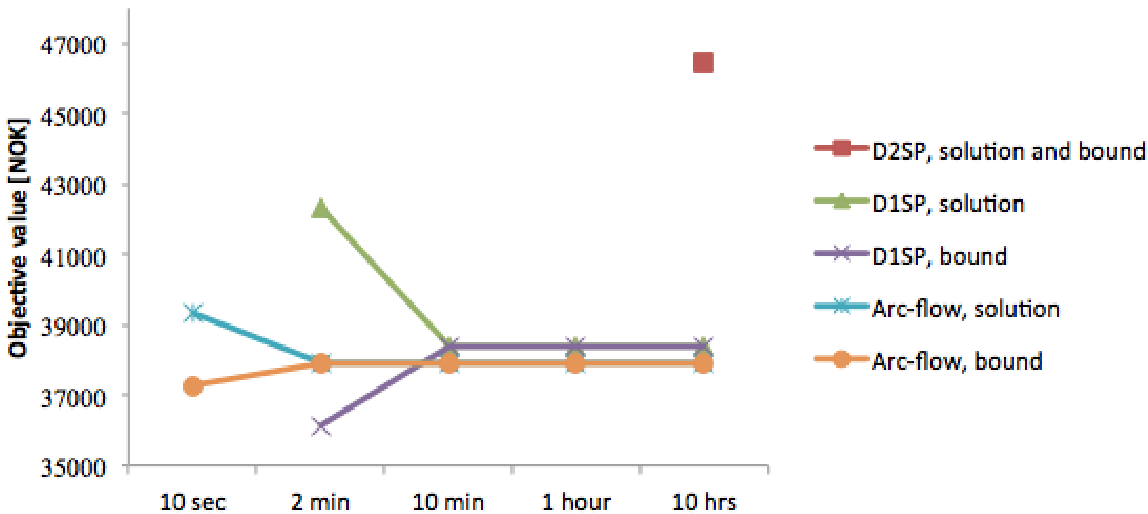
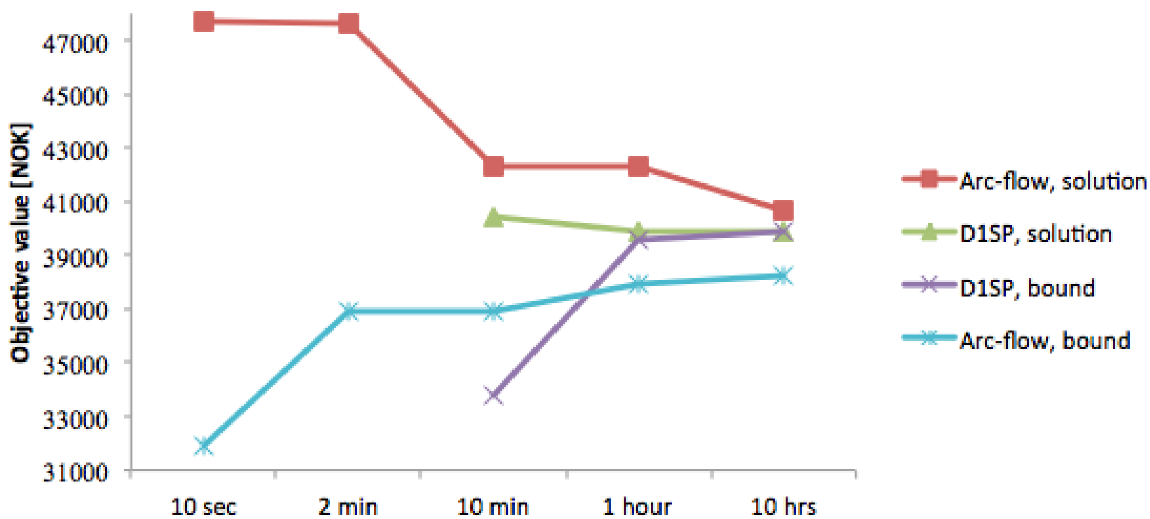


Figure 19: *Objective value and bound after different runtimes for N2*



20 minutes, but it takes more than 9 hours to close it. This is due to the slow convergence of the B&B algorithm. D2SP is not able to find a feasible integer solution to the larger instance within ten hours due to the large number of vehicle-route combinations searched through between each fixation of vehicles to routes. Table 23 shows the best integer solutions found by each model for each instance.

The D1SP model gives a 1.26% worse solution for instance N1 than the arc-flow model, but a 1.97% better solution for N2. D2SP gives a 22.5% worse solution to N1 than the arc-flow model, and cannot find a feasible solution to N2.

The results from this section demonstrate that D2SP provides the best LP bounds for both instances. However, this model is not able to find good integer solutions. As mentioned in

Table 23: *Best integer solutions provided by each model for both instances*

	N1	N2
Arc-flow	37918	40653
D1SP	38397	39854
D2SP	46449	-

9.2.2, the main reason for this is that inadequate production schedules are found to match the delivery patterns. Even though optimal delivery patterns are found, the correct schedules are not generated. The problem lies in that the coordination between the PAS-SP and VR-SP is not good enough. The fixing strategy implemented in Section 9.2.2 improves the coordination but the gaps for the resulting integer solutions are considerable. To find optimal integer solutions an algorithm that applies column generation in each node in the B&B tree is necessary.

Another drawback with D2SP is the long computational time due to the vast number of vehicle-route combinations. For future work it could be interesting to look at how the solution time can be reduced further, e.g. it could help to resolve the PAS-SP several times without solving the VR-SP after a sufficient amount of delivery patterns are generated. However, solving the MIP for the PAS-SP can also become quite time consuming for bigger instances where the production scheduling is tighter. In this case an analysis of the underlying structure of the PAS-SP must be done to find alternative solution approaches.

Another alternative is to solve the VR-SP using dynamic programming for larger instances. Pre-generation of routes is very useful when there are many restrictions on the routes, e.g. time windows, loading or sequencing constraints. For our problem the only restrictions are the time windows and so for instances with many customers there will be very many feasible routes.

The arc-flow model is better at finding feasible solutions on small instances like N1, while D1SP is the better choice for larger instances like N2. This is true with regards to computational time, size of MIP gap and objective value. D1SP also provides a better LP bound than the arc-flow model. A small drawback with the D1SP model is the slow convergence it experiences towards closing the MIP gap entirely. We want to investigate the larger instance N2 further in our economic analysis, and based on the findings in this section we choose to use the D1SP model to perform this analysis.

Due to the more complex master problem in D1SP this model will in theory not be able to solve as large problems as the more decomposed D2SP model. D2SP also provides a far better LP bound than D1SP. For future work it would therefore be interesting to continue with D2SP and apply a Branch and Price algorithm in order to find optimal solutions with this model.

10 Economic Analysis

The newspaper industry in Norway needs to reduce costs or increase revenues to reverse the negative trend seen the last decade. Declining sales and advertising revenues have hit the industry hard, and all the media groups are considering every aspect of their business. Through conversations with Amedia and Schibsted we have chosen three current topics to analyze the economic effects of. First we evaluate if there is a positive value of cooperation, before we look at the effects of changing printing technology from traditional offset to modern digital. Digitalizing is interesting not only from a cost perspective, but it could also increase the advertising revenues since it allows for highly customized newspapers to small groups of readers. Lastly effects of moving the newsroom deadline are analyzed. Because of the reduced value of last-minute news in printed papers, moving the deadline is more relevant than ever.

We compare costs for both media groups, so all savings and values found are for Amedia and Schibsted combined. The larger instance (N2) is used for all the analyses.

10.1 Value of cooperation

As described in Chapter 2, Amedia and Schibsted are already cooperating within distribution. However, there is no cooperation with respect to printing, and they are especially competitive in the South-Eastern part of Norway. Regardless, decreased demand for printed newspapers has led to an excess capacity in printing facilities in this area today, and cooperation between the media groups could be beneficial.

We wish to study if there is a value in cooperating with regards to both printing and distribution for Amedia and Schibsted. To do this we evaluate two cases, one with full cooperation and one with no cooperation in printing. The latter case is the situation today for the facilities we are considering in Stokke and Nydalen. The case with full cooperation implies that all products can be printed in and routed from both facilities.

Even though our model has the option of shutting down facilities, we do not consider this in this case study. This is mainly because we do not consider all the products produced in both facilities and can therefore not say whether a facility should be closed based on our findings. In addition, it is somewhat unrealistic to look at closing of facilities in the medium term, but in the long term this could be more interesting. The decision of which facilities to keep open does in any case include more dimensions than our model incorporates, e.g. market power, capacity for future demand and non-newspaper products, etc.

When considering no cooperation we lock production of Schibsted products (Aftenposten and VG) to Nydalen, and Amedia products (Drammens Tidende, Fredriksstad Blad, Moss Avis, Tønsbergs Blad and Varden) to Stokke by adding equalities (10.1)-(10.2) to the model formulation. One facility cannot produce the other media group's products, where P^A and P^S are the sets of Amedia and Schibsted products, respectively.

$$\sum_{m \in M} \sum_{t \in T} g_{2mtp} = 0 \qquad p \in P^A \tag{10.1}$$

$$\sum_{m \in M} \sum_{t \in T} g_{1mtp} = 0 \qquad p \in P^S \tag{10.2}$$

Table 24 summarizes the results, all costs are in NOK.

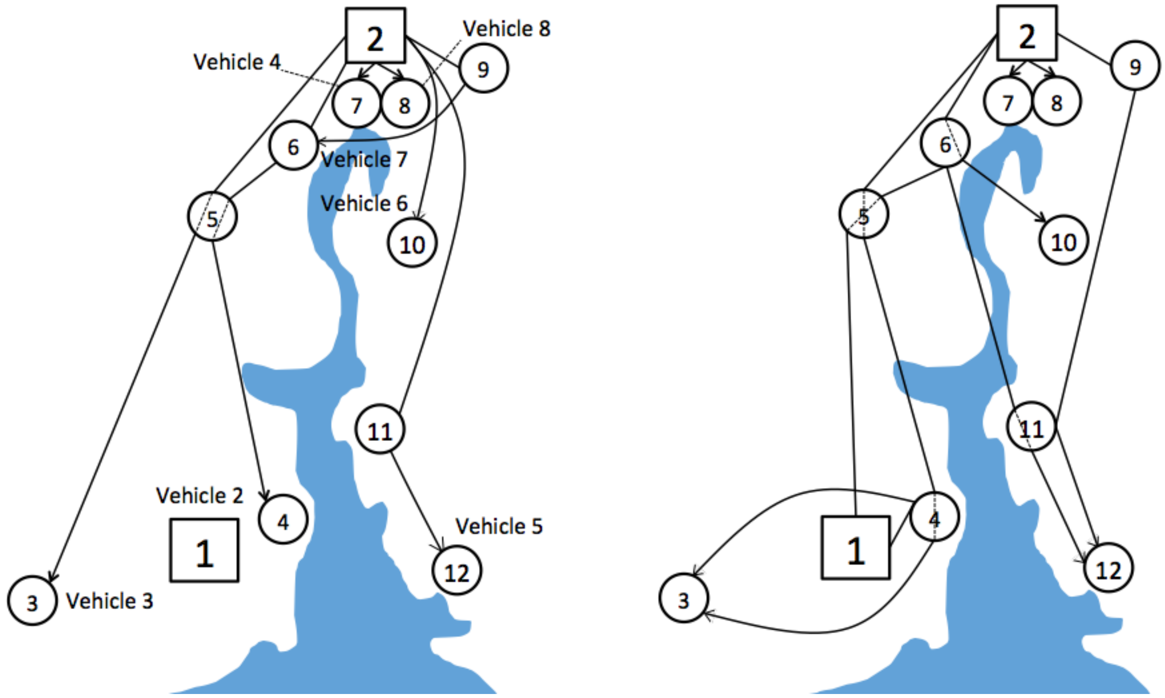
Table 24: *Full cooperation vs. no cooperation. Costs and distance.*

	No Coop	**Coop**
Total cost	41048	39855
Change	-	-3 %
Distribution cost	13048	11855
Change	-	-9 %
Distance [km]	1182	898
Change	-	-24 %

We see that there lies significant value in cooperation for Amedia and Schibsted. Distribution costs are reduced by 9%, due to improved vehicle routing. The number of vehicles utilized are seven in both cases, so these savings consists of a shorter total distance driven, since fixed vehicle costs are the same. This distance is reduced with as much as 24% when we look at full cooperation. In both cases only one set of printing plates is needed for each product, so savings in total costs are only due to savings in routing and are therefore 3%.

The different routing solutions are presented in Figure 20. Between customer 6 (Asker&Bærum) and customers 10 (Ski) and 11 (Moss) the bridge between Drammen and Ski is used. Which vehicle uses which route is included in the routing for full cooperation because we will link it to the production schedule shown below.

There is a demand for Schibsted products VG and Aftenposten in all of the customer nodes, which implies that without cooperation vehicles from Nydalen have to visit all customers. The demand for Amedia products are smaller and without cooperation as much as four customers are visited on one route from Stokke. When we open up for cooperation it is better to move the smaller Amedia products to Nydalen, and add these products to the vehicles leaving from Nydalen to every customer node with VG and Aftenposten anyways.



(a) Vehicle routing with full cooperation (b) Vehicle routing with no cooperation

Figure 20: *Differences in routing for the cases with and without cooperation*

Figure 21 shows the production schedule with full cooperation. Stokke is not included since it is not in use.

Figure 21: *Production scheduling for base case with full cooperation*

		Facility 2 (Nydalen)	
		Press 1	Press 2
	21:00	VG	FB
	21:30		
	22:00	DT	AP
	22:30		AP
	23:00	TB	
Vehicle 3	23:30		V
	00:00	VG	
Vehicle 2	00:30	VG	MA
	01:00	VG	
Vehicle 4 & 5	01:30		AP
	02:00		AP
Vehicle 7	02:30		AP
Vehicle 6 & 8	03:00		AP
	03:30		

AP: Aftenposten
DT: Drammens Tidende
FB: Fredriksstad Blad
MA: Moss Avis
TB: Tønsberg Blad
V: Varden
VG: Verdens Gang

This production schedule only presents the sequencing of products with necessary changeover time. Products may be produced in later time slots since there is excess production capacity even when all products are moved to Nydalen. Our model does not minimize delivery time, but constrains delivery within time windows at each customer. Excess production capacity can then lead to sequencing with longer changeovers than the minimum time of one timeslot. However, this is inconsequential since the important information from a production point of view is the allocation of products to facilities, in which sequence the products are produced and for how long. When the different vehicles leave the facility is shown left of the schedule.

With full cooperation all products are printed at Schibsted's printing facility in Nydalen. This is due to the economies of scale with offset printing, since startup costs are high and per unit cost diminishes with large production volumes. The lower production rates in Stokke means that Nydalen has to print at least one product, and reduced routing distances from Nydalen leads to the solution that all products should be printed there. When offset printing is used these results indicate that cooperation leads to a more centralized production of newspapers.

A positive value of cooperation seems reasonable, since it is more preferable to choose the optimal printing location from a selection of facilities rather than being locked to one location for each media group. Printing several products at the optimal location can enable the mix of products in each vehicle to be better with respect to which customers should be visited to minimize routing. Without cooperation the mix of products in each vehicle are more constrained by which products are produced at the facility the vehicle leaves from, and the routing is compromised. Only one set of printing plates is used per product in both cases, so there are no savings in production costs. With less overcapacity in the printing facilities, there could have been an even larger value of cooperation if it enabled facilities to shift away from producing products simultaneously on different presses due to time constraints.

We conclude that full cooperation between Amedia and Schibsted can lead to significant reductions in distribution costs due to more optimal routing of vehicles. The distance driven is reduced by 24% and one can argue that besides financial savings this has positive environmental effects. There are several other aspects to consider with full cooperation, e.g. cost savings from rationalizing the production. A higher level of efficiency with respect to labor, utilities, materials, etc. could be possible to obtain when cooperating, but this is outside the scope of this thesis.

The case with full cooperation will be our base case in the rest of the economic analysis, because this case is more interesting to use for evaluating the effects of digitalization and moving deadlines.

10.2 Effect of digitalizing the printing process

In this section we analyze the effects of changing from offset printing to digital printing. The printing rates for digital printers are significantly lower than for offset printing. Modern digital printers have a print rate of approximately 10000 newspapers per hour compared to realistically 60000 per hour for offset printing [Kringler and Larsen, 2013]. With both Stokke and Nydalen open it is not possible to produce the total demand and deliver within the delivery deadline with the current digital print rates. There have, however, been significant improvements within digital printing technology the last decade and assuming that this development will continue it could be interesting to investigate what the effects of digital printing would be if the production rates were higher. We consider a case where the print rate is 20000 newspapers per hour.

Digital printing eliminates many of the mechanical steps required for offset printing, such as producing printing plates and manually fastening these to the printing towers. When using digital printers the changeover time between products is virtually zero. For offset printing there are fixed costs associated with each run, consequently the unit cost goes down as the quantity goes up. For digital printing on the other hand the cost is relatively steady, irrespective of how many copies that are printed of an edition [Mejtoft, 2005]. This leads to lower per unit costs for very small print runs compared with offset printing. These effects are captured in our model by the plate cost associated with offset printing and removing the plate cost for digital printing.

By removing the changeover time and plate costs from the model, in addition to reducing the production rate, we can investigate the effects of digitalizing the printing process. Other costs associated with printing (e.g. cost of paper, ink, labour and maintenance) are assumed to be similar and are therefore not included in the analysis. To fully realize the effect of digitalization the possibility of printing products in different locations must exist, so the testing is run on the case where full cooperation between the media groups is assumed.

Table 25: *Production allocation with offset printing vs digital printing*

	Facility 1	**Facility 2**
Offset Printing	Not used	Aftenposten Drammens Tidende Fredriksstad Blad Moss Avis Tønsbergs Blad Varden VG
Digital printing	Aftenposten Drammens Tidende Tønsbergs Blad Varden VG	Aftenposten Fredriksstad Blad Moss Avis VG

Table 25 demonstrates the shift in production allocation when converting to digital printing. The production sequencing using digital printers is illustrated in Figure 22 and the routing is presented in Figure 23.

Figure 22: Production schedule with digital printing

	Facility 1 (Stokke)		Facility 2 (Nydalen)	
	Press 1	Press 2	Press 1	Press 2
21:00	VG	V	AP	AP
21:30	VG	VG	VG	MA
22:00	VG	VG	VG	VG
22:30	DT	VG	FB	FB
23:00	DT	AP	MA	AP
23:30	AP	DT	VG	VG
00:00	TB	AP	AP	AP
00:30	V	VG	AP	AP
01:00	TB	AP	VG	VG
01:30		TB	AP	AP
02:00			AP	AP
02:30			VG	VG
03:00			AP	AP
03:30			AP	AP

AP: Aftenposten
DT: Drammens Tidene
FB: Fredrikstad Blad
MA: Moss Avis
TB: Tønsberg Blad
V: Varden
VG: Verdens Gang

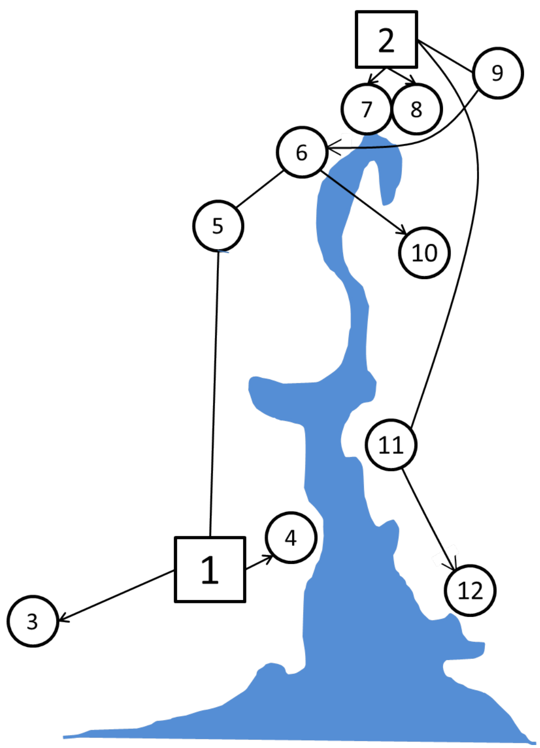


Figure 23: *Vehicle routing with digital printing*

With plate costs and changeover times removed from the model the number of changeovers between products increases and several of the products are printed in different locations and on different presses at the same time. We see for example that both VG and Aftenposten are now printed in both facilities. Digitalization of the printing allows for more flexibility in the sequencing of production and results in smaller batches of editions, which in turn leads to more flexibility for products that have to be transported further to be produced first (e.g. the products that are delivered to Fredrikstad and Moss from Nydalen are produced first). This allows for more cost efficient routing. Compared with offset printing, one can say that digitalization decentralizes the printing processes. This is the opposite effect of what we observed from evaluating full cooperation using offset printing technology. If digital presses are given, one can say that cooperation does not centralize production, but rather optimizes the routing by printing different products as close to the customers as possible. This is due to the fact that only distribution costs are being minimized.

Table 26 presents the differences between distribution costs and kilometers driven for the case of full cooperation using offset printing vs digital printing. The distribution costs are reduced by 7.5% due to a 24% reduction in the total kilometers driven. As mentioned in the previous section, in addition to reducing costs, the reduced fuel consumption also leads to less emissions to the environment.

Table 26: *Difference in distribution costs for offset vs. digital printing*

	Offset printing	**Digital printing**
Distribution costs [NOK]	11854	10961
Change	-	-7,5 %
Distance [km]	898	685
Change	-	-24 %

In addition to reduced distribution costs there are other factors that need to be taken into consideration when evaluating the effects of changing to digital printing. One of the great advantages of digital printing is the possibility of changing each individual print during a job, e.g. customizing each newspaper with marketing material directed at groups of readers or individuals.

The case tested here includes major newspapers and few printing facilities. The effects of digitalization are likely to be even more visible in a case with additional and more geographically dispersed printing facilities as well as more geographically dispersed demand, e.g. looking at all of Norway and including all small local newspapers. It is worth mentioning that cooperation between Schibsted and Amedia therefore increases the effects of digitalization. Due to the current production rates, combined with virtually non-existing changeover times between products, and relatively low per unit cost for small batches, digital printing is currently best suited for printing editions with low circulation numbers.

The biggest obstacle for changing to digital printers today is the print rate, but if the technology is further developed and production rates are increased, converting to digital print can lead to more efficient routing and reduced distribution costs. The cost savings and advantages of customizing newspapers should be compared with the investment costs when considering making a shift towards digitalizing the printing process.

10.3 Effect of moving newsroom deadline

In this section we investigate the value of moving the editorial deadline. When media corporations evaluate their supply chain the production departments negotiate deadlines with the different newspapers. The newsroom deadline determines when production of newspapers can start, so from a production and distribution point of view earlier editorial deadlines are desirable. The newsrooms, on the other hand, wish to have a late deadline to increase the editorial value of the newspaper by including the latest news. However, as mentioned in Chapter 2, the pressure to include last-minute news has decreased with the increase in online publishing. Breaking news stories are reported continuously online which is creating a shift in the way newsrooms work. There is a constant pressure for the online editions to be up-to-date on last minute news and this has taken some of the pressure off the printed editions. The content in printed editions is shifting towards including more and more feature pieces, which can be written further in advance, than breaking news stories. As a result, earlier deadlines have become a realistic possibility. Earlier production starts would give more flexibility in the production and distribution part of the supply chain, which in turn could allow for more efficient distribution and potential cost savings. Consequently, evaluating the effect of moving deadlines is a very relevant topic.

In the case we have studied in the previous sections, where there is full cooperation and offset printing, there is such an overcapacity that the effects of moving deadlines both forward and backward are hard to see. When moving the deadlines from 9 PM to 6 PM all products are still produced in Nydalen. The routing is the same as for the original deadline and consequently distribution costs are unchanged. Although no change is found in the routing there may be other benefits to starting production earlier. Moving deadlines forward would lead to production being finished earlier in general, thus providing a larger time window for distribution and a lower probability of missing delivery deadlines due to unforeseen events. Unpredictable incidents such as machinery break downs or traffic accidents may lead to unforeseen and costly delays. Delays can be expensive both in terms of additional costs, such as overtime pay, as well as loss of revenue due to cancelled subscriptions. Earlier deadlines would provide a time buffer for delays and would be beneficial regardless of the facilities' production capacity. Our model is deterministic and has hard time windows, so uncertainty that could lead to late deliveries and penalties for delays are not captured by the model.

As both digital printing and earlier deadlines are relevant topics being considered by the media corporations today we will analyze the effects of moving the deadlines in the case of digital printing presented in the previous section. This will serve as a base case for analyzing the effects of moving editorial deadlines. In addition, through comparing the findings with the results from using offset printing in Section 10.1 we can also study the combined effect of digitalization and moving editorial deadlines.

We look at moving the newsroom deadline forward to 8 PM, 7 PM and 6 PM, and for the sake of comparison, pushing it back to 10 PM. The base case for this analysis is modelled with full cooperation, 9 PM production start, no plate cost, digital print rates and changeover times removed. We move the deadline for all the seven products. The model includes product specific newsroom deadlines, so it would also be possible to change the deadline for only some of the products. However, to see the isolated effect of earlier deadlines we continue using equal newsroom deadlines.

Table 27 presents the differences between distribution costs and kilometers driven for different newsroom deadlines. We see that when moving the deadline forward the distribution costs are reduced. This is due to the fact that the earlier deadlines allow for better production allocation with respect to the distribution. The customers are now served from the facility that is closest to them to a higher degree.

Table 27: *Difference in costs and distance driven for different deadlines*

Newsroom deadline	6:00 PM	7:00 PM	8:00 PM	9:00 PM	10:00 PM
Distribution costs [NOK]	10429	10429	10726	10961	11494
Change	-4,9 %	-4,9 %	-2,1 %	-	5 %
Distance [km]	558	558	628	685	812
Change	-18,5 %	-18,5 %	-8,3 %	-	18,6 %

The production sequencing found when the newsroom deadline is moved forward to 6 PM is illustrated in Figure 24 and the routing is presented in Figure 25 (the routing and sequencing of production is the same for the 7 PM production start). The earlier deadline allows for all of the demand in customer 5 (Drammen), customer 10 (Ski) and customer 6 (Asker&Bærum) to be produced and distributed from Nydalen instead of Stokke. This results in more efficient routing and a 5% reduction in distribution costs due to a 18.5% reduction in the distance driven compared to the case with 9 PM deadline.

Figure 24: *Production schedule for 6 PM production start*

	Facility 1 (Stokke)		Facility 2 (Nydalen)	
	Press 1	Press 2	Press 1	Press 2
18:00	AP	AP	FB	FB
18:30	VG	VG	AP	DT
19:00	TB	VG	VG	VG
19:30	AP	TB	AP	AP
20:00	VG	TB	AP	AP
20:30	V	VG	VG	VG
21:00		VG	AP	MA
21:30		V	AP	VG
22:00		VG	AP	DT
22:30		VG	MA	AP
23:00			AP	AP
23:30			VG	VG
00:00			VG	VG
00:30			DT	AP
01:00			AP	VG
01:30			AP	AP
02:00			AP	VG
02:30			VG	
03:00				
03:30				

AP: Aftenposten
DT: Drammens Tidene
FB: Fredrikstad Blad
MA: Moss Avis
TB: Tønsberg Blad
V: Varden
VG: Verdens Gang

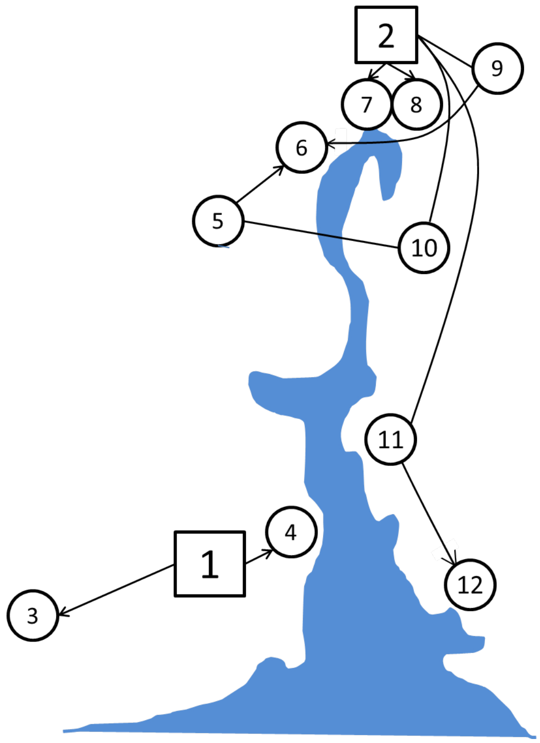


Figure 25: *Vehicle routing with digital printing and 6 PM newsroom deadline*

For the 8 PM deadline there is enough capacity in Nydalen to produce all of the demand for customer 10 (Ski) and customer 6 (Asker&Bærum), but not enough for the entire demand destined for customer 5 (Drammen), so this is produced in Stokke. This leads to a 2.1% reduction in cost.

The later deadline of 10 PM results in a 5% increase in costs. When pushing the deadline back to 10 PM all but one time slot are needed to produce all of the demand and the resulting production allocation and sequencing is less efficient with respect to routing. Nydalen produces only VG and Aftenposten for its closest customers 6-10 (Asker&Bærum, Western Oslo, Eastern Oslo, Lillestrøm and Ski). Customers 11 and 12 (Moss and Fredrikstad) have to be served from Stokke by ferry.

In conclusion, moving deadlines has a considerable impact on production allocation, and consequently distribution costs, when the production capacity and demand are relatively equal. Cost savings found through moving editorial deadlines should also be considered in relation to the estimated reduction in editorial value.

When comparing the base case situation of using offset printing and 9 PM newsroom deadlines to the case with both digital printing and earlier deadlines we see a 12 % reduction in distribution costs due to more efficient allocation of production and routing. The total kilometers driven are reduced by a 38%. This leads to the conclusion that a combination of earlier deadlines and digital printing may give rise to substantial cost savings if implemented in the future. The results can be seen in Table 28.

Table 28: *The combined effect of moving deadline and digital printing*

	Offset printing and 9 PM	**Digital printing and 7 PM**
Distribution costs	11854	10429
Change	-	-12 %
Total kilometers driven	898	558
Change	-	-38 %

An interesting notion is that moving deadlines forward produces different effects for offset printing and digitalization. Moving the deadline forward provides a bigger time-window for production. When offset printing is used this will lead to a higher degree of centralization in order to take advantage of the opportunity for economies of scale. For offset printing this will always be the case as long as the savings in production costs outweigh the increase in distribution costs. For digital printing, on the other hand, the main goal will always be to optimize the distribution and so products will be allocated so as to minimize the distance driven within the restrictions given by production and vehicle capacity.

As mentioned earlier in this section, moving newsroom deadlines forward is not unrealistic, although the large newspapers often have editorial deadlines as late as 11 PM many smaller local newspapers already have deadlines as early as 6 PM. With the current trend of online publishing and the pressure for last-minute news in printed editions decreasing, the content of printed newspapers may be very different in the future. However, it is perhaps not as realistic to shift production of all products to digital printers. This is due to the low cost-per-unit when high volumes are printed with offset technology. The effects seen from digitalization will however still be present if some of the smaller editions could be printed digitally.

11 Conclusion

Technical analysis

We have identified that column generation procedures that add fewer columns per iteration reduce the solution time for the root node considerably for both of the decomposed path-flow models. The way in which vehicles and routes are ordered for solving the VR-SPs also influences the solution time. Which procedure is best depends on the structure of the problem, for D2SP the best results are found when adding 10 or less columns per iteration for all orderings, while for D1SP the best results are more dependent on the ordering.

The best column generation procedures for D2SP reduce the solution time of the root node by 52%. For D2SP it is important to find a good balance between the number of columns added per iteration and the total number of iterations. This also means to find a balance between patterns created and schedules created. For D1SP, which strategy leads to the shortest solution time depends both on the number of columns added to the RMP in each iteration and also in which order the VR-SP is solved for combinations of vehicles and routes. The best strategy overall with respect to solution time is found when going through all routes per vehicle (K, R) and adding 100 columns per iteration. This leads to a reduction in solution time of 77 % compared to adding all columns with negative reduced cost in each iteration. The column generation strategies are more effective for D1SP than for D2SP. This is due to the fact that for D2SP the PAS-SP effects the number of iterations, and hence solution time, and the procedures we have tested affect only the column generation in the VR-SP.

When solving D2SP by B&B after the root node has been solved without generating new variables none of the column generation procedures lead to feasible integer solutions. This is due to the fact that insufficient production schedules are created to cover all the demand when the IP is solved. In order to create better schedules the communication between the PAS-SP and VR-SP is improved by successively fixing vehicles to routes and reapplying column generation. Through fixing vehicles to routes the integer solution is greatly improved and feasible integer solutions are found. Although the best solution still has a considerable gap we find a pessimistic bound through applying a fixing strategy that allows for column generation after the root node.

For D1SP, solving the IP through general B&B provides feasible solutions regardless of which column generation procedure has been used. The solution found using D1SP improves the pessimistic bound found with D2SP by 15% for instance N1. Fixing strategies that generate new columns after successively fixing vehicles to facilities or routes do not improve the integer solution for D1SP. The delivery patterns generated in the LP relaxation after applying fixing strategies are still not sufficient to find an improved integer solution. The reason this fixing solution is effective for D2SP is because by fixing vehicles to routes the coordination of the two subproblems is improved. For D1SP however, the PAS is included in the MP and so the coordination between the two subproblems is better to start with. In order to generate the complete columns to find the optimal IP solution a full Branch and Price algorithm could be implemented.

When comparing the different models we find the arc-flow model to be superior with respect to finding feasible solutions on small instances, while D1SP is the better choice for larger instances. This is true with regards to computational time, size of MIP gap and objective value. D1SP also provides a better LP bound than the arc-flow model. D2SP provides a far better LP bound than both the arc-flow formulation and the D1SP, but does not lead to feasible integer solutions without the use of fixing strategies. For future work it would therefore be interesting to continue with D2SP and apply a Branch and Price algorithm in order to find feasible solutions with this model, especially since the complex nature of the master problem in D1SP limits the size of possible problem instances it is able to solve.

Economic analysis

Through a case study we have found that cooperation between Amedia and Schibsted with regards to printing can lead to significant reductions in distribution costs due to more optimal routing. The total distance driven is reduced by 24% compared to the case where Amedia products are printed in Stokke and Schibsted products in Nydalen. Distribution costs are reduced with 9%, which is less than the reduction in distance driven due to equal fixed vehicle costs. When using offset printing technology, cooperation leads to a more centralized production in order to minimize production costs by taking advantage of economies of scale.

Digitalization of the printing process allows for more flexibility in the allocation and sequencing of production due to lower set-up costs. This allows for more cost efficient routing with a more decentralized production closer to the end-customer. This effect is larger with cooperation between media groups due to more geographically disperse facilities and customers. The largest obstacle for changing to digital printers today is the print rate. However, if the technology is further developed and production rates are increased, converting to digital print can lead to more efficient routing and reduced distribution costs.

Moving deadlines forward produces different effects for offset printing and digitalization. Moving deadlines has a considerable impact on production allocation, and consequently distribution costs, when the production capacity and demand are relatively equal. Moving the deadline forward provides a bigger time window for production. When offset printing is used this will lead to a higher degree of centralization in order to take advantage of the opportunity for economies of scale in the production. For offset printing this will always be the case as long as the savings in production costs outweigh the increase in distribution costs. For digital printing, on the other hand, the main goal will always be to optimize the distribution and so products will be allocated so as to minimize the distance driven.

When comparing the base case (with cooperation) of using offset printing and 9 PM newsroom deadlines to the case with both digital printing and earlier deadlines we see a 12 % reduction in distribution costs due to more efficient allocation of production and routing. The total kilometers driven are reduced by a 38%. This leads to the conclusion that a combination of earlier deadlines and digital printing may give rise to substantial cost savings if implemented in the future. In addition to cost savings, reducing the distance driven has a positive environmental effect; the reduced fuel consumption also leads to less emission to the environment.

The economical analysis showed positive values and effects for all of the topics we evaluated.

However, there are some obstacles that should be taken into consideration in each case. Co-operation is not necessarily beneficial with respect to strategic aspects like market power, positioning for future demand, etc. Digitalizing the printing process is not viable at the moment, and even with increased printing rates this could involve a potentially large investment for an uncertain future market. With that said, the decentralizing effects of digital printing could bring many smaller, now shut down, printing facilities back to life. Lastly, even though printed newspapers are not the main provider of last minute news anymore, it could reduce the editorial value further if deadlines are moved forward. The printed newspaper is after all still the most important product for printing facilities, and it is vital that customers keep appreciating it.

12 Future Work

This section presents possible directions for further research. Future work can be directed at considering solution methods that find optimal integer solutions to the path-flow models, and extending the model and instances to include even more realistic aspects.

For D2SP, when solving the LP relaxation small fractions of schedules can be used which leads to low production costs. To improve the LP bound the option of adding valid inequalities could be explored, e.g. since every product has to use at least one set of printing plates, inequalities that ensure this could be given attention.

As mentioned throughout the thesis, in order to guarantee optimal integer solutions to the decomposed path flow models a full Branch and Price algorithm could be implemented. D2SP provides a far better LP bound than D1SP, in addition to decomposing the problem more. For future work it would therefore be interesting to continue with D2SP and apply Branch and Price in order to find optimal solutions with this model.

The model can be extended in order to consider a more realistic representation of the newspaper industry. Although the mathematical model is fairly flexible with regards to taking in different problem variations (e.g. heterogeneous vehicle fleet, production rates dependent on both products and presses, etc.), the instances on which we have tested the models are simplified. A possible option for future work is to expand the instances that we have considered to looking at additional printing facilities and all products in Eastern Norway, or the entire country. This would require access to extensive input data such as demand for all local newspapers. In addition, some changes can be made to the model to make it more realistic. The changeover times between production of different products could be modelled in a way that better reflects the actual time it takes to change printing plates. The changeover times would then vary depending on which two products the change is between. Further extensions could be to include multiple trips for vehicles and incorprate the reverse logistics of returning unsold newspapers. These extensions would complicate the model and increase the computational effort needed to solve larger instances. There will always be a trade-off between the degree of reality in the model and the size of the instances that can be solved.

As mentioned in Section 9.4, for large instances both the PAS-SP and VR-SP may become time consuming to solve. For future work it could therefore be interesting to look at how the solution time can be reduced further. For example by using dynamic programming in the VR-SP or investigating alternative solution approaches to the PAS-SP by analyzing the underlying structure of the problem, e.g. decomposing into subproblems for each press as well. Adding more symmetry-breaking constraints should also be explored further, especially with respect to vehicles and presses.

APPENDIX

A Grouping of Arc-flow Constraints

Production allocation and scheduling constraints

$$min \sum_{i \in I^F} C_i^F f_i + \sum_{i \in I} \sum_{p \in P} C^P h_{ip} \tag{A.1}$$

$$M_i^M f_i - \sum_{m \in M} \sum_{p \in P} g_{impt} \geq 0 \qquad i \in I^F, t \in T \tag{A.2}$$

$$h_{ip} - \sum_{m \in M} g_{impt} \geq 0 \qquad i \in I^F, p \in P, t \in T \tag{A.3}$$

$$\sum_{p \in P} g_{impt} \leq 1 \qquad i \in I^F, m \in M, t \in T \tag{A.4}$$

$$S_{im}(1 - g_{imp(t-1)}) - \sum_{\rho \in P \setminus p} \sum_{\tau = t}^{t+S_{im}-1} g_{im\rho\tau} \geq 0 \qquad i \in I^F, m \in M, t = 2, \ldots, N^T, p \in P \tag{A.5}$$

$$\sum_{m \in M} R_{imp} g_{impt} - \sum_{k \in K} q_{ipkt} \geq 0 \qquad i \in I^F, t \in T, p \in P \tag{A.6}$$

$$\sum_{t \in T} \sum_{p \in P} q_{iktp} \leq Q_k \qquad i \in I^F, k \in K \tag{A.7}$$

$$g_{imtp} \in \{0, 1\} \qquad i \in, m \in M, t \in T, p \in P \tag{A.8}$$

$$q_{iktp} \geq 0 \qquad i \in I, k \in K, t \in T, p \in P \tag{A.9}$$

Vehicle routing constraints

$$min \sum_{k\in K}\sum_{t\in T} C_k^V x_{kt} + \sum_{i\in I}\sum_{j\in I}\sum_{k\in K} C_{ijk}^D w_{ijk} \tag{A.10}$$

$$y_{ik}^N - y_{ipk}^C \geq 0 \qquad i \in I^C, k \in K, p \in P \tag{A.11}$$

$$\sum_{t\in T} x_{kt} - y_{ipk}^C \geq 0 \qquad i \in I^C, k \in K, p \in P \tag{A.12}$$

$$\sum_{i\in I^F} Q_k y_{ik}^N - \sum_{i\in I^C}\sum_{p\in P} D_{ip} y_{ipk}^C \geq 0 \qquad k \in K \tag{A.13}$$

$$\sum_{t\in T} x_{kt} \leq 1 \qquad k \in K \tag{A.14}$$

$$\sum_{i\in I^F}\sum_{j\in I^C} w_{ijk} - \sum_{t\in T} x_{kt} = 0 \qquad k \in K \tag{A.15}$$

$$\sum_{i\in I\setminus j} w_{ijk} - y_{jk}^N = 0 \qquad j \in I, k \in K \tag{A.16}$$

$$\sum_{i\in I} w_{ijk} - \sum_{i\in I} w_{jik} = 0 \qquad j \in I, k \in K \tag{A.17}$$

$$t_{jk} - \sum_{t\in T} U_t x_{kt} - T_{ijk} w_{ijk} + M^{D1}(1 - w_{ijk}) \geq 0 \qquad i \in I^F, j \in I^C, k \in K \tag{A.18}$$

$$t_{jk} - t_{ik} - T_{ijk} w_{ijk} + M^{D2}(1 - w_{ijk}) \geq 0 \qquad i \in I^C, j \in I^C, k \in K \tag{A.19}$$

$$A_i \geq t_{ik} \geq B_i \qquad i \in I^C, k \in K \tag{A.20}$$

$$y_{ik}^N \in \{0,1\} \qquad i \in I, k \in K \tag{A.21}$$

$$y_{ikp}^C \in \{0,1\} \qquad i \in I, k \in K \tag{A.22}$$

$$w_{ijk} \in \{0,1\} \qquad i \in I, j \in J, k \in K \tag{A.23}$$

$$x_{kt} \in \{0,1\} \qquad k \in K, t \in T \tag{A.24}$$

$$s_k \geq 0 \; and \; integer \qquad k \in K \tag{A.25}$$

$$t_{ik} \geq 0 \; and \; integer \qquad i \in I, k \in K \tag{A.26}$$

Connecting constraints

$$\sum_{i \in I^F} y_{ik}^N \leq 1 \qquad k \in K \qquad (A.27)$$

$$\sum_{k \in K} y_{ik}^N \geq 1 \qquad i \in I^C \qquad (A.28)$$

$$\sum_{k \in K} y_{ikp}^C = 1 \qquad i \in I^C, p \in P | D_{ip} > 0 \qquad (A.29)$$

$$\sum_{i \in I^F} \sum_{t \in T} q_{ipkt} - \sum_{i \in I^C} D_{ip} y_{ipk}^C \geq 0 \qquad k \in K, p \in P \qquad (A.30)$$

$$Q_k y_{ik}^N - \sum_{t \in T} \sum_{p \in P} q_{ipkt} \geq 0 \qquad i \in I^F, k \in K \qquad (A.31)$$

$$Q_k(1 - x_{kt}) - \sum_{i \in I^F} \sum_{\tau = t+1}^{T} \sum_{p \in P} q_{ik\tau p} \geq 0 \qquad k \in K, t \in T \qquad (A.32)$$

B Full Model Formulation for D1SP

B.1 Master Problem

Sets and indices

I	Set of nodes i
I^C	Subset of customer nodes i
I_r^C	Customers visited in route r
I^F	Subset of production facility nodes i
M	Set of printing presses $m = 1, \ldots, N^M$
K	Set of vehicles k
T	Set of time slots $t = 1, \ldots, N^T$
P	Set of products p
S	Set of schedules s
R	Set of routes r
R_i^F	Set of routes starting in facility i
W	Set of product patterns w

Parameters

Y_{ir}^N	1 if node i is visited on route r
T_{ks}^F	Time slot when vehicle k is finished loading on schedule s
T_{kr}^S	Time slot when vehicle k at the latest can start route r
C_{kr}^R	Cost of vehicle k driving route r
C_{is}^S	Cost of facility i using schedule s
Y_{ipkrw}	1 if product p is delivered to customer i by vehicle k on route r with pattern w, 0 otherwise
Q_{ipkts}	Quantity of product p loaded onto vehicle k at production facility i in time slot t with schedule
Q_{iks}	1 if vehicle k is loaded at production facility i with schedule s
D_{ip}	Demand of product p at node i
M_i^L	Maximum quantity loaded in a time slot at facility i
C^P	Cost of producing printing plates
R_{imp}	Production rate at facility i on press m for product p
S_{im}	The number of time slots required for a product change on press m in facilty i

Decision Variables

λ_{krw}	Binary variable 1 if vehicle k drives route r with pattern w
q_{ik}	Binary variable 1 if vehicle k is loaded at production facility i
q_{ipkt}	The quantity of product p loaded onto vehicle k at production facility i in time slot t
g_{impt}	Binary variable 1 if product p is produced on press m in at facility i in time slot t
h_{ip}	Number of printing plate sets needed to print product p at facility i
t_{ikt}^L	Binary variable 1 if vehicle k is loaded in time slot t
t_{ik}^F	Time slot when vehicle k is finished loading

$$min\ z = \sum_{i \in I^F} C^F f_i + \sum_{i \in I^F} \sum_{p \in P} C^P h_{ip} + \sum_{k \in K} \sum_{r \in R} \sum_{w \in W} C_{kr}^R \lambda_{krw} \tag{B.1}$$

$$N^M f_i - \sum_{m \in M} \sum_{p \in P} g_{impt} \geq 0 \qquad i \in I^F, t \in T \tag{B.2}$$

$$\alpha_{ip}| \quad \sum_{k \in K} \sum_{r \in R} \sum_{w \in W} Y_{ipkrw} \lambda_{krw} \geq 1 \qquad i \in I^C, p \in P | D_{ip} \geq 0 \tag{B.3}$$

$$\beta_{jpk}| \quad \sum_{t \in T} q_{jpkt} - \sum_{i \in I^C} \sum_{r \in R_f} \sum_{w \in W} D_{ip} Y_{ipkrw} \lambda_{krw} \geq 0 \qquad j \in I^F, p \in P, k \in K \tag{B.4}$$

$$\gamma_{ik}| \quad \sum_{r \in R_f} \sum_{w \in W} Y^N_{ir} \lambda_{krw} - \sum_{s \in S} q_{ik} \geq 0 \qquad i \in I^F, k \in K \tag{B.5}$$

$$\epsilon_{ik}| \quad \sum_{r \in R_f} \sum_{w \in W} T^S_{kr} \lambda_{krw} - t_{ik} \geq 0 \qquad i \in I^F, k \in K \tag{B.6}$$

$$\eta_k| \quad \sum_{r \in R} \sum_{w \in W} \lambda_{krw} \leq 1 \qquad k \in K \tag{B.7}$$

$$q_{ik} - g_{impt} \geq 0 \qquad i \in I^F, m \in M, p \in P, k \in K, t \in T \tag{B.8}$$

$$h_{ip} - \sum_{m \in M} g_{impt} \geq 0 \qquad p \in P, t \in T \tag{B.9}$$

$$\sum_{p \in P} g_{impt} \leq 1 \qquad m \in M, t \in T \tag{B.10}$$

$$\sum_{t \in T} \sum_{p \in P} q_{ipkt} \leq H_k \qquad k \in K \tag{B.11}$$

$$S_{im}(1 - g_{imp(t-1)}) - \sum_{\rho \in P \setminus p} \sum_{\tau = t}^{t + S_{im} - 1} g_{im\rho\tau} \geq 0 \qquad m \in M, p \in P, t = 2, \ldots, N^T \tag{B.12}$$

$$\sum_{m \in M} R_{imp} g_{impt} - \sum_{k \in K} q_{ipkt} \geq 0 \qquad p \in P, t \in T \tag{B.13}$$

$$M^L_i t^L_{kt} - \sum_{p \in P} q_{ipkt} \geq 0 \qquad k \in K, t \in T \tag{B.14}$$

$$\sum_{p \in P} q_{ipkt} - t^L_{kt} \geq 0 \qquad k \in K, t \in T \tag{B.15}$$

$$t^F_k - \tau t^L_{k\tau} \geq 0 \qquad k \in K, \tau \in T \tag{B.16}$$

$$\lambda_{krw} \in \{0, 1\} \qquad k \in K, r \in R, w \in W \tag{B.17}$$

$$g_{imtp} \in \{0, 1\} \qquad i \in I, m \in M, t \in T, p \in P \tag{B.18}$$

$$h_{ip} \in \{0, 1\} \qquad i \in I, p \in P \tag{B.19}$$

$$q_{ik} \in \{0, 1\} \qquad i \in I, k \in K \tag{B.20}$$

$$t^L_{kt} \in \{0, 1\} \qquad k \in K, t \in T \tag{B.21}$$

$$t^F_k \geq 0 \; \textit{and integer} \qquad k \in K \tag{B.22}$$

$$q_{iktp} \geq 0 \qquad i \in I, k \in K, t \in T, p \in P \tag{B.23}$$

B.2 Vehicle Routing Subproblem

Parameters

C_{kr}^{R} Cost of vehicle k driving route r
Y_{ir} 1 if node i is in route r
H_k Capacity of vehicle k

Decision Variables

y_{ipkr} Binary variable 1 if product p is delivered to customer i by vehicle k on route r
$\bar{c}_{kr}$ Reduced cost of vehicle k using route r

$$min\ \bar{c}_{kr} = C_{kr}^{R} - \sum_{i \in I^C} \sum_{p \in P} \bar{\alpha}_{ip} y_{ipkr} + \sum_{i \in I^C} \sum_{p \in P} \bar{\beta}_{jpk} D_{ip} y_{ipkr} - \bar{\gamma}_{jk} - T_{kr}^{S} \bar{\epsilon}_{jk} - \bar{\eta}_k \tag{B.24}$$

$$\sum_{p \in P} y_{ipkr} \geq Y_{ir} \qquad i \in I_r^C \tag{B.25}$$

$$\sum_{i \in I_r^C} \sum_{p \in P} D_{ip} y_{ipkr} \leq H_k \tag{B.26}$$

$$y_{ipkr} \in \{0,1\} \qquad i \in I, p \in Pk \in K, r \in R \tag{B.27}$$

C Digital Attachments

A folder is attached on DAIM with the following items:

- Implementation of arc-flow model, arcflow.mos
- Implementation of D1SP model, D1SP.mos
- Implementation of D2SP model, D2SP.mos
- Input files for all models and all instances
- Result files from comparison of models
- The Master's thesis itself, both as .pdf and LaTeX

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