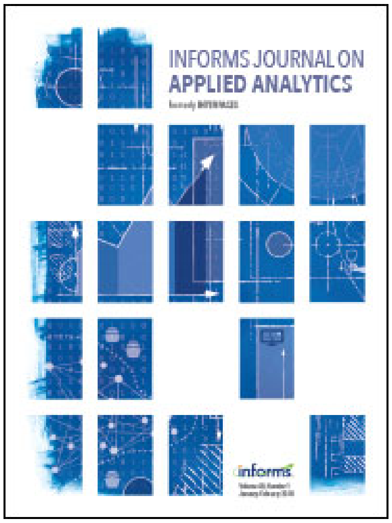

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A Decision-Making Tool for a Regional Network of Clinical Laboratories

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For healthcare systems that operate in large, geographically dispersed areas, the quality of the services provided requires the effective management of a complex transportation problem. We present a decision support system to help healthcare managers improve the delivery of biological samples collected from patients in hospitals and outpatient clinics to laboratories that perform tests on them. We develop an optimization model for supporting strategic decisions on the transport of samples and the assignment of work in a large healthcare network with geographically dispersed hospitals, clinics, and testing laboratories. We embed our model in a Web-based tool to provide planners with interactive functions, enabling them to explore solutions and interactively access data to facilitate the analysis of what-if scenarios. The tool proved invaluable in helping the Andalusian Healthcare System obtain significant improvements in efficiency, quality of service, and outsourcing costs.

Key words: decision support; clinical laboratories network; production and transportation planning; mixed integer programming; graphic decision tool.
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In the Andalusian autonomous region of southern Spain, the Andalusian Health Administration (AHA) provides universal public health services to more than eight million people. Because of increasing cost constraints, healthcare planners such as AHA need to enhance their decision-making processes to prudently allocate their available resources. In 2008, AHA undertook an ambitious project for the Andalusian Regional Network of Clinical Laboratories (RNCL) to implement new processes to meet this objective. RNCL's new paradigm focuses on coordination within its laboratories, development of service level agreements, and integration of laboratory information systems.

Clinical laboratories within RNCL provide laboratory test services that are crucial to the quality of patient healthcare. These services are an integral part of diagnosis, therapy, and patient care, including risk screening in healthy patients. The process starts with collecting a biological sample from a patient at any laboratory within RNCL's extensive peripheral network. RNCL may test this specimen within its network or may outsource the analysis; we refer to this analysis as test processing or determination. After the processing laboratory has completed its clinical tests, it sends the results to the laboratory that collected the sample. Plebani et al. (2006) describe the sequence of tasks involved. To aid its operational decisions, AHA periodically issues a report with an estimate of the processing cost of each determination as performed by each laboratory (i.e., the result of a biennial cost-control technique based on relative value units as commonly used in public hospitals) (Brezmes et al. 2002).

In early 2008, AHA appointed a multidisciplinary committee, including healthcare managers, clinicians, and operations research engineers, to develop strategies to improve the services of RNCL. After studying comprehensive internal reports on RNCL's prior activities in this area, the committee reached three major conclusions. First, it determined that in the absence of a planning procedure to assign work to laboratories, factors such as provincial boundary issues, aggressive marketing from private laboratories, and personal relationships often influenced the choice of the processing laboratory for a test. The lack of coordination among laboratories led to a general pattern of individualistic behavior within RNCL, resulting in an unnecessarily high number of outsourced determinations. Moreover, although RNCL had a sufficient number of fully equipped member laboratories capable of performing the tests, the outsourcing costs were one of the highest components in its service delivery costs.

Second, the committee concluded that shipping costs were excessive. In the context in which RNCL managers were negotiating new price structures, including pricing for reactive products (i.e., products that interact with specimens to facilitate measurements of the requested parameters) and laboratory information systems, shipping services had to be included in these price structures. To obtain better prices and higher quality from the carrier services, the committee decided to centralize its procurement of package carrier firm contracts.

Third, healthcare managers and clinicians on the committee were confident that RNCL's laboratories could handle larger workloads, and some hospitals should limit the traffic (i.e., annual quantity of tests shipped) they send to their preferred or favorite higher-level hospitals.

After the committee completed its analysis, it identified two action items. It would develop (1) a new reference model (i.e., paradigm), which would be based on a business process management platform, to facilitate cooperation among laboratories and track tests within RNCL, and (2) a new planning procedure to better utilize RNCL's laboratories and reduce the number of outsourced tests. This procedure would focus on coordination and improved logistics. Our research group was responsible for developing this planning procedure, the major output of which is the decision support system (DSS) that we discuss in this paper.

We structured this paper as follows. The *Problem Description* section outlines the problem for which RNCL planners required a new planning procedure. The *Literature Review* section presents a brief review of the literature related to the problem. The *RNCL's Long-Term Planning Problem* section describes the modelling assumptions within our proposal to support all-inclusive managerial decisions for RNCL's logistics. The *Model* section describes our solution, a mixed-integer linear programming (MILP) model (see Appendix A). We perform a sensitivity analysis on different parameters of the model to study its viability to fit a variety of likely midterm scenarios (see Appendix B). The section *DSS Tool Implementation* presents a Web-based interactive tool developed to implement the MILP model and hence, fulfill the quantitative analysis requirement dictated by RNCL management (i.e., the use of an accessible and user-friendly software tool). Finally, *Conclusions* summarizes the major results of our work and discusses future work.

Problem Description

The clinical laboratories at RNCL are located inside hospital buildings or in separate buildings within or near the hospital complex. The core healthcare network includes about a dozen reference hospitals that have large central laboratories equipped with total laboratory automation systems (e.g., advanced analytical and information technology (IT) techniques), which are capable of providing results covering many parameters. Although their portfolios include more than 1,400 clinical tests, we can observe a Pareto distribution of the clinical tests requested. Extraneous tests make up about 10 percent of the tests; according to Schleicher (2006, p. 125), "… about 10 percent of the requests are scattered over a wide variety of very different parameters which are requested only in specialized cases." The core healthcare network also includes provincial hospital laboratories, which are not equipped as extensively and often redirect clinical tests to other processing laboratories.

After the committee completed its analysis, it encouraged healthcare managers to implement changes to improve both efficiency and the general quality of patient care. The committee believed that the enhanced cooperation among member laboratories would result in clear benefits to patients because test results would be received earlier. Additionally, healthcare managers needed comprehensive quantitative analyses to make informed decisions about efficiency improvements. Because the RNCL portfolio was comprehensive, savings were possible if healthcare managers undertook both strategic and design improvements throughout RNCL. Using decision tools to assess the alternatives for enhanced coordination and logistics in this large and complex network would be necessary. Specifically, because RNCL had opened new facilities as part of a general plan to improve access to medical care (Rodríguez Diaz 2011), planners needed a tool to respond to events in the changing RNCL environment. For example, a planner must consider that in setting up new hospitals, a hospital may come online (i.e., be activated) although its laboratory is still part of RNCL. The DSS had to be an IT tool that would address three requirements, as follows.

(1) It must be able to use input data from diverse sources to construct and resolve different scenarios, regardless of the amount of computer time needed.

(2) It must allow planners to analyze the workload and the flow assignments by studying a resolved scenario (i.e., midterm plan) in greater detail.

(3) It must allow planners to compare scenarios. The tool must allow them to rank each potential plan based on the average expected satisfaction of patients, as if the potential plan had been in practice. Planners must be able to use the tool to make operating decisions on primary care—the RNCL service that drains the most resources.

Literature Review

We began our review of previous literature by considering the core models of network design (Ahuja et al. 1993). Next, we reviewed work that addresses problems similar to those that RNCL faced.

Because of the difficulties of maintaining stable conditions for biological samples, decisions on transportation and samples processing are similar to those needed in the supply chain of perishable goods. Ekşioğlu and Jin (2006) address a production and transportation planning problem in a two-echelon supply chain for a single perishable product, which they model as a flow network to which the authors add a MILP formulation. However, their model does not consider transportation between the facilities, and enforces the constraint that each retailer is assigned to exactly one facility. Ekşioğlu et al. (2007) use the same approach, but they extend it to a multiproduct model. They solve it using Lagrangian decomposition, although they do not assume that goods have a limited life. However, their work does not consider production and (or) transportation capacity constraints, as required by RNCL planners (e.g., limiting the traffic from provincial hospitals to higher-level hospitals, and considering the capacity of the latter).

Because the RNCL planning problem relates largely to the transportation between nodes (i.e., hospitals or clinical laboratories), we reviewed studies that address the perishable nature of goods and focused on the transportation stage. Andreatta and Lulli (2008) consider a real-world application of blood delivery from a blood bank to hospitals within a city; they model it as a multiperiod travelling salesman problem. Osvald and Stirn (2008) formulate a problem of perishable food distribution as a vehicle routing problem time window with time-dependent travel times. Ambrosino and Sciomachen (2007) determine the distribution plan for two products (fresh food and frozen food) to minimize the total travelling costs by formulating a vehicle routing problem with split delivery. These three works use a directed graph structure, which is also appropriate to represent the RNCL logistical issues. Nevertheless, they are not applicable to the RNCL problem, because they are suitable only for small networks and do not consider production decisions.

In analyzing the logistical issues of RNCL, we characterize it as various clinical sample types travelling through a distribution network; thus, we choose to regard it as a multicommodity network-flow problem (MCF). Therefore, we formulate it as a multicommodity minimum-cost flow problem, using link selection and flow assignment as decision variables, and cost minimization as its objective. It differs from standard minimum-cost flow problems in that we consider the cost of the flow along each link as a discrete function of the flow along that particular link. Cohn et al. (2008) use a similar approach to deal with the cost reduction achieved by a package carrier firm when contracting with a cargo airline; they assume that the cargo airline presents a price offer to each client depending on the cost of the entire load purchased. However, in Cohn et al. (2008), discounts on shipments are a function of the overall flow of the network; in our study, we use discount factors attached to the flow in each connection. Moreover, the carrier firm network comprises fewer than

50 nodes; we must manage a much larger network of almost 500 nodes in the RNCL planning problem. Therefore, our method of quantifying savings in each link of the network represents an innovation in current research—and an even greater innovation when applied to RNCL's large network.

RNCL's Long-Term Planning Problem

Our planning procedure focuses on the task of reengineering and redesigning RNCL's planning problem (henceforth referred to as the planning problem). We tackle it by considering long-term planning with a deterministic data approach, thereby equalizing seasonal issues over the long term.

We create an MCF model explained in a graph of RNCL. In this model, the flow through a vertex incurs a processing cost (if the sample is analyzed) or a transhipment cost. Our model also includes costs for flowing along links, whether they represent shipping costs or outsourcing costs.

Graph Representation

To provide a flexible representation of the network, we identify the following functional entities:

- Serving center (SC): the clinical laboratory (vertex) that processes tests on samples; its main feature is its installed capacity.
- Outsourcing center (OC): a single entity that models the service points located outside the RNCL boundaries.
- Point of extraction (POE): the center that collects samples for analysis; it could be within RNCL (in an SC) or outside RNCL (in the OC).
- Demand transfer point (DTP): the center at which samples coming from POEs are collected (a process that involves reception, stabilization, and conservation); the samples are shipped later—typically to an SC.

We next represent RNCL by using a directed graph (see Figure 1), that contains $N+2$ vertices: N vertices represent the centers (i.e., SCs, POEs, DTPs), an artificial vertex represents the individual demand insertion point (i.e., the supersource vertex that supplies the total demand for the planning horizon) that feeds the POEs, and another artificial vertex represents the sink vertex for the outsourcing flows. For sample stability, if the distances between vertices are excessive (>250 km), we exclude shipping connections.

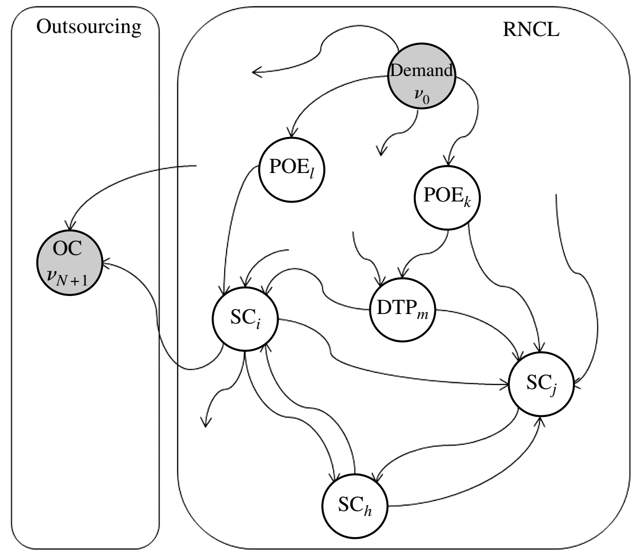

Figure 1: This directed graph represents the regional network of clinical laboratories. Biological samples collected at points of extraction (POEs) are shipped to demand transfer points (DTPs) or service centers (SCs) for analysis, or to an outsourcing center (OC).

Model

We develop a MILP model that takes into account the specific requirements relevant to the planning problem, to find where to best satisfy the demand for clinical tests (i.e., process the clinical samples) and how to best route them, with the primary objective of minimizing operational costs. Appendix A provides the detailed formulation of the planning problem.

The objective function includes both the aforementioned costs (shipping, transhipment, processing, and outsourcing) and two additional factors that contribute to operational costs. Planners want to prevent an excessive number of transhipments between laboratories to avoid additional operational costs (see Figure 2). These additional costs are a piecewise linear function of transhipments. The threshold that triggers this penalty is expressed as a percentage of the installed capacity, and the penalty has a linear relationship to the number of transhipments above the threshold. However, planners also want to ensure that workloads are above a specific minimum level when they select a clinical laboratory for processing a particular test type. Therefore, we add a second piecewise linear function that includes a penalty whenever the

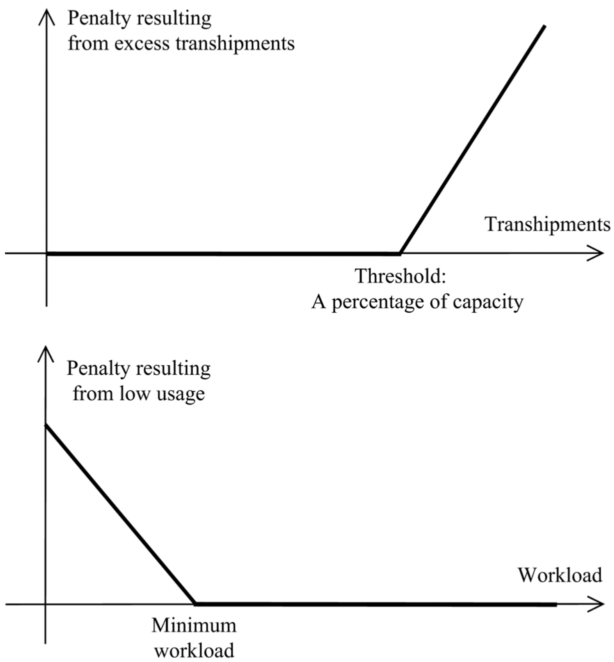

Figure 2: A laboratory that receives too few or too many samples to analyze incurs additional operational costs. When it receives too many samples, a penalty results from the excessive number of transhipments; however, when it receives too few samples, a penalty results from the inadequate use of installed capacity.

established minimum workload at an RNCL laboratory is not achieved (see Figure 2). In this figure, we assume that the penalty, because of this low usage, follows a piecewise linear function of the workload. The penalty has a linear relationship to the workload deficit.

Our model sets the per-unit shipment cost along each link as a discrete function of the flow along that link. RNCL managers negotiate discounts based on volume using a public tender for which carrier firms bid. To simplify the tender process, each carrier must present a single price offer for each shipping connection (i.e., offer the same set of discount rangesfor each link), with each range characterized by a lower bound, an upper bound, and the discount rate. Reciprocally, the firms winning the tender may save costs by using aggregation (i.e., carrying more freight in a single shipment). Therefore, our model considers the cost of flow along each shipping connection; it first bases the cost on distance and later discounts the price depending on the flow and carrier choice.

Using the previous modelling assumptions, we transform the RNCL planning problem into one of obtaining a detailed production and transportation plan to minimize operational costs (i.e., we assign specific workloads to each SC, select only one package carrier company to operate each link, and stipulate the exact number of each test type that can flow through each link).

Finally, to fully realize the production and transportation plan that has been generated, the model estimates the expected quality of service (QoS). QoS is measured in terms of an average geographical accessibility (AGA) indicator, which indicates the average number of transhipments each test needs to reach the laboratory that will process the sample (see Equation (A18)). This ad hoc indicator considers that each transhipment involve tasks (i.e., reception, conservation, storage, and resending of clinical samples) and has a risk that the sample might deteriorate because of temperature or time. Clearly, a plan with a low AGA value would provide good geographical accessibility performance and timely test results.

The model allows the decision maker to impose traffic bounds (constraints (A6) and (A7)) and capacity constraints for the processing levels, including the outsourcing vertex (constraints (A3)). It uses typical MCF balance equations for the workload assignment to vertices and for the evaluation of transhipments in each SC (constraints (A4) and (A5)). As mentioned earlier, the model supports centralized management of package carrier services (constraints (A8) and (A10)). Finally, the penalty shapes in Figure 2 appear linearized (constraints (A11)–(A16)).

Sensitivity Analysis

The model focuses initially on the current RNCL planning problem. However, extending and adapting it to other contexts (e.g., the addition of new care services or centers, or demographic changes) is possible. Therefore, a sensitivity analysis of various parameters of the problem will provide insights about the viability of the model for different scenarios.

In approaching the sensitivity analysis, we use design of experiments (DOE) (Montgomery 2009) to fine-tune the estimate of the real influence of parameters using a reduced number of experiments.

Consequently, we apply a systematic variability of parameters (factors) and then carefully investigate the effects of those factors in the observable outputs (responses). Appendix B shows our DOE sensitivity analysis.

We group the parameters of our analysis into three sections, as we describe next.

(1) Parameters related to the optimization tool: the *Tlimit* parameter indicates the computation time that the tool requires to optimally solve the model. Planners might have to optimally solve multiple scenarios within one session; hence, short computation times can be critical in designing an interactive and responsive tool.

(2) Model parameters: the use of the DSS tool for informed decision making requires that we adjust the following three model parameters to settings that the planners recommend: the penalty for inadequate use, the penalty for excessive transhipments, and the threshold that triggers these penalties.

(3) Network topology: by using three network topology parameters, we attempt to reflect different types of networks and scenarios. The size parameter defines the scope and complexity of the network, reflecting the structure of two geographic areas: provincial and regional levels. The other two network topology parameters capture the extent of variability in demand and capacity to be considered in generating the instances of the various scenarios. Specifically, they are the coefficients of variation for the stochastic distributions applied to randomly generate demand and capacity samples, respectively.

In determining the effects, we consider the following responses: the costs reported by the model or objective function, the geographic accessibility indicator, the outsourcing level, and the MIP gap relative to the optimal solution. Although we can foresee the influence of some of these factors in the responses, we cannot easily estimate these impacts by a cursory inspection; therefore, our analysis quantifies the relative impact of each factor on each response.

Based on a statistical examination of the sensitivity analysis results, we conclude the following:

• All responses are affected by at least two parameters.

• All parameters have a significant effect (not attributable to error) on the responses; the exception is the threshold for triggering the penalty because of excessive transhipments, which only moderately affects the quality of the solutions.

In addition, we list some additional conclusions that allow us to give more practical insights to the decision maker, as follows.

• The parameter with the greatest effect on both the total costs and the degree of accessibility is network size. Its influence on the computational quality of the solution obtained by the solver software exceeds that of the time limit. This means that the regional nature of the RNCL network is the critical factor in determining the suitability of the DSS tool for RNCL planning, even if the decision maker uses long resolution times. Hence, this conclusion justifies the validity of the shortened-computation-time hypothesis to provide planners with an interactive and responsive DSS tool.

• The outsourcing level does not depend on the network size, which means that the model provides consistent results as it attempts to minimize outsourcing. Moreover, outsourcing is affected mainly by capacity dispersion. This shows that inadequate capacity distribution may cause outsourcing to appear more affordable.

• The degree of accessibility (i.e., the expected QoS) is affected by all the parameters, excluding the threshold for triggering the penalty from excessive transhipments. This indicates that the expected QoS is sensitive to the parameter settings. Therefore, RNCL planners can be confident that the estimated degree of accessibility is consistent and will enable them to rank each potential plan that the DSS tool generates.

In summary, the results of the sensitivity analysis indicate that both DSS real-time usability and suitability to the RNCL plan are affected mainly by network size. Furthermore, the embedded model offers considerable flexibility to allow decision makers to implement a variety of policies because of the sensitivity of the expected QoS to the parameter settings.

DSS Tool Implementation

The committee launched a collaborative pilot project to implement a DSS tool in conjunction with the new RNCL planning approach. The objective was to generate a plan for the service that consumes the most RNCL resources: the provision of laboratory tests for primary care. The RNCL authorities assisted us by providing data, sharing the business rules of RNCL, and providing access to technical staff from the regional government, the Junta de Andalucía, including specialists from the geographical information systems department, cost controllers, and clinical personnel. They also increased awareness and overcame any resistance to change by extolling the importance of improved coordination in managing RNCL through in situ briefings to RNCL personnel affected by the project.

Framework Architecture

We coded the RNCL planning model in AMPL (Fourer et al. 2003) to create a core computational application (i.e., optimization engine), which reads input data from a relational database that contains data collected from RNCL, computes the solution by resolving the large-scale MILP described in the section *RNCL's Long-Term Planning Problem*, and places the solution into the same database.

We packaged the optimization engine as a component of a Web-based DSS that uses state-of-the-art IT tools to allow planners to revise input data, change parameter settings, run the planning model, and perform detailed analyses of the plans generated. We embedded an interactive graphical user interface (GUI) to facilitate these steps and allow the user to generate the appropriate RNCL annual production and transportation plan.

We coded the GUI using the PHP server-side scripting language, which allows planners to run the optimization engine and shows them a graphical representation of the output solutions based on the Google Maps API. The GUI allows the user to revise or modify the plan and to project and analyze what-if scenarios by changing data from the relational database to create new scenarios. The DSS provides user-friendly tools to enable the user to study a resolved scenario in greater detail and save it for future study or comparison, making it possible to compare two archived scenarios.

In addition to the Google Maps API standard functionalities (e.g., zoom, drag), our graphical representation of solutions is characterized by various icons (see Figure 3). It uses larger triangles (laboratories with higher values for the displayed decision variable) and thicker lines (links with heavy traffic for the displayed layer commodity k) for easier identification of issues. In addition, interactive access to a resolved scenario is possible by clicking on a specific laboratory (i.e., displaying its workload variable values) or by clicking on a specific link (i.e., displaying its flow variable values), as Figure 3 illustrates.

Exploiting the DSS

The RNCL planners extensively used our DSS to determine which subset of the available new facilities to activate in 2009 (Rodríguez Diaz 2011). In 2009, we also provided consultancy services for planning the primary care service, based on historical data from 2008, and on the RNCL network map for the facilities scheduled to be opened. Historical performance data from 2009 showed that this service had greater geographical coverage and QoS; in addition, costs fell from eight million euros in 2008 to 0.2 million euros in 2009, primarily because of reduced outsourcing costs.

The graph under discussion consisted of 488 vertices and 2,477 links, whereas we considered six commodities (i.e., groups of test types suggested by managers). The controlling parameters, which we derived from the decision-makers' preferences, were (1) excess transhipment penalties of 50 euros with a trigger at 120 percent of capacity, and (2) penalties of 10 euros when the designated workload did not meet 10 percent of installed capacity.

Conclusions

Efficiency and cost containment are essential elements in healthcare service provision. In Andalusia, AHA launched a project to analyze RNCL's processes and make appropriate changes to improve their efficiency and quality of care. The recommended organizational changes are (1) a new reference model to facilitate cooperation among laboratories, and (2) centralized management of logistics based on a new RNCL planning procedure that focuses on the optimum use of its fully equipped laboratories and a reduction in the number of outsourced tests.

This paper investigates a new planning method to enhance logistics management within RNCL and provide planners with a DSS tool to conduct quantitative

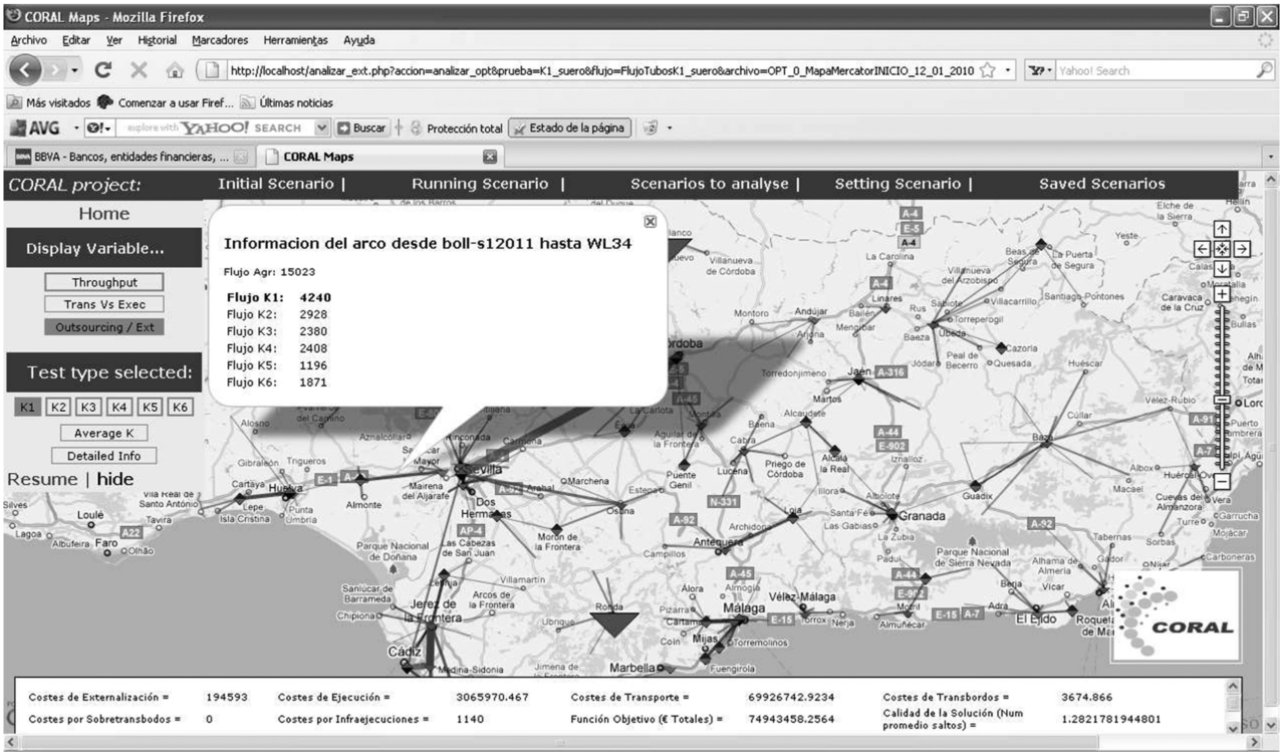

Figure 3: The DSS provides a user-friendly interface based on the Google Maps API to allow a user to explore a solution.

analysis before reassigning resources, redistributing charges, or reorganizing flows. This innovative application is based on network-flow modelling that uses a MILP formulation. Its implementation is characterized by a user-friendly GUI to exploit an optimization engine based on AMPL. Under the conditions we tested, the MILP is a huge problem with about 47,000 variables, of which 14,300 are binary, and approximately 36,000 constraints. Our experience shows that obtaining the exact resolution for the RNCL planning problem is challenging. Although the DSS users are satisfied with the approximated solutions generated (using commercial solvers Gurobi 2.2 and CPLEX 11, the gap to the optimum is less than 10 percent after 1,800 seconds of computation time), we must investigate ways to speed up the computations.

We leave the exploration of more efficient solution techniques for future work. This future work could include algorithms based on Benders decomposition—separating the complicating variables z_{ij}^{rg}, which disrupt the network-flow structure—or on constructive heuristics procedures that could provide good results by starting with a feasible solution. Another possibility for future work is a time-based addition to study the provision of other services: specialized, critical, and emergency care. Depending on the type of service required, we could identify two primary delivery modes—express or regular mode (Andreatta and Lulli 2008). Express mode would be associated with urgent demands that must be met within 24 hours; regular mode (i.e., the remaining demands) could have a more flexible response time (typically two–four days). The inclusion of the time factor would compel us to use space-time network models (Clark et al. 2004, Cohn et al. 2007, Durbin and Hoffman 2008, Marín 2006, Marín and Codina 2008, Yan et al. 2006). We could load the RNCL routing problem with both urgent and regular requests, and determine which requests must be serviced immediately and which can be satisfied later. However, this extension would undoubtedly require modifications to the existing GUI.

Appendix A. Mathematical Formulation

Sets of Indices

- $\bar{V}$ Set of vertices in graph $\bar{G} = (\bar{V}, \bar{L})$, with elements: $v_i \in \bar{V}$, $i = \{0, \ldots, N+1\}$.
- $\bar{L}$ Set of links in graph $\bar{G} = (\bar{V}, \bar{L})$, with elements: $(v_i, v_j) \in \bar{L} \mid v_i, v_j \in \bar{V},\ i = \{0, \ldots, N\},\ j = \{1, \ldots, N+1\}$.
- V Set of vertices representing real-life centers, with elements: $v_i \in \bar{V}$, $i = \{1, \ldots, N\}$. These are all the vertices in $\bar{V}$, except the demand insertion vertex v_0 and the outsourcing vertex v_{N+1}.
- L Set of links representing real shipping connections, with elements: $(v_i, v_j) \in \bar{L} \mid v_i, v_j \in \bar{V},\ i = \{1, \ldots, N\},\ j = \{1, \ldots, N\}, i \neq j$.
- S_j Set of indices marking the successors of vertex j: $S_j = \{m \mid \exists (v_j, v_m) \in \bar{L}\}$.
- P_j Set of indices marking the predecessors of vertex j: $P_j = \{m \mid \exists (v_m, v_j) \in \bar{L}\}$.
- G Set of package carrier companies considered for shipping services: $g \in G \mid g = 1 \ldots N_g$. There are N_g different carriers.
- R^g Set of discount ranges offered by carrier g: $r \in R^g$. The discounts depend on the traffic committed to each shipping connection $(v_i, v_j) \in L$, if assigned to be operated by g. These ranges fully partition the feasible volume of total flow on each link: L^{rg} and U^{rg} are the lower and upper bounds, respectively, on this flow for the discount range r, and DF^{rg} is the discount factor.
- K Set of clinical tests types: $k \in K \mid k = 1 \ldots N_k$.

Model Parameters

- a_{ik} Number of type k tests demanded by vertex $v_i \in V$, with nonzero values only for POEs.
- C_{ik} Upper bound to the number of type k test determinations produced by vertex $v_i \in \bar{V}$ (i.e., installed capacity). Nonzero values are applicable for only the executor vertices: OC and SC.
- c_{ik}^{E} Processing cost of type k tests in vertex $v_i \in V$: fixed per-unit-based cost with nonzero value applicable only for the executor vertices: OC and SC.
- c_{ij}^{S} Shipment costs based on distance for link $(v_i, v_j) \in L$.
- c_{ik}^{SOC} Externalization (outsourcing) costs of type k tests purchased by vertex $v_i \in V$.
- c_{ik}^{T} Transhipment costs in the ith vertex of type k tests, because of fixed per-unit-based inventory cost in each $v_i \in V$.
- u Percentage to apply to C_{ik} to obtain the threshold that triggers a penalty because of excessive transhipments.
- p Per-unit penalty when excessive transhipments occur.
- Y_{ij} Upper bound for aggregated traffic through link $(v_i, v_j) \in L$.
- S_{ijk} Upper bound for a type k traffic through link $(v_i, v_j) \in L$.
- W_{ik} Minimum workload with nonzero values applicable only for vertices $v_i \in V \mid C_{ik} > 0$.
- p^{low} Per-unit penalty when the established minimum workload W_{ik} is not met.
- L^{rg} Lower bounds on flow for discount range r offered by carrier g.
- U^{rg} Upper bounds on flow for discount range r offered by carrier g.
- DF^{rg} Discount factor offered by carrier $g \in G$ to be applied if the total flow committed in a specific link is in $[L^{rg}, U^{rg}]$ (i.e., in range $r \in R^g$).
- M A large number, well above any possible number of transhipments (i.e., an upper bound for the number of transhipments).

Variables

- e_{ik} Number of type k test determinations to be produced in vertex $v_i \in \bar{V}$ (i.e., workload assignment).
- s_{ijk} Number of type k tests flowing through link $(v_i, v_j) \in \bar{L}$.
- t_{ik} Number of type k test transhipments in vertex $v_i \in V$.
- α_{ik}^{OT} 1, if $v_i \in V$ is above the threshold for the penalty trigger ($t_{ik} > u \cdot C_{ik}$) and consequently, in the excessive transhipment range for type k tests; 0 otherwise.
- t_{ik}^{OT} t_{ik}, if $\alpha_{ik}^{OT} = 1$; 0 otherwise.
- β_{ik}^{LW} 1, if $v_i \in V$ does not meet the minimum workload for type k tests ($e_{ik} < W_{ik}$); 0 otherwise.
- e_{ik}^{LW} e_{ik}, if $\beta_{ik}^{LW} = 1$; 0 otherwise.
- z_{ij}^{rg} 1, if aggregated flow on link $(v_i, v_j) \in L$ is operated by carrier g, with the discount for range $r \in R^g$; 0 otherwise.
- y_{ij}^{rg} Number of tests flowing on link $(v_i, v_j) \in L$, shipped by carrier g, and priced based on the discount factor for range $r \in R^g$.

The model is then:

$$
\begin{aligned}
\min \quad Z = {} & \sum_{v_i \in V} \sum_{k \in K} c_{ik}^{SOC} \cdot s_{i(N+1)k} \\
& + \sum_{g \in G} \sum_{r \in R^g} \sum_{(v_i, v_j) \in L} c_{ij}^{S} \cdot (1 - DF^{rg}) \cdot y_{ij}^{rg} \\
& + \sum_{k \in K} \sum_{v_i \in V} c_{ik}^{E} \cdot e_{ik} + \sum_{k \in K} \sum_{v_i \in V} c_{ik}^{T} \cdot t_{ik} \\
& + \sum_{k \in K} \sum_{v_i \in V \mid C_{ik} > 0} p \cdot (t_{ik}^{OT} - u \cdot C_{ik} \cdot \alpha_{ik}^{OT}) \\
& + \sum_{k \in K} \sum_{v_i \in V \mid C_{ik} > 0} p^{\text{low}} \cdot (\beta_{ik}^{LW} \cdot W_{ik} - e_{ik}^{LW}),
\end{aligned}
$$

$$\text{s.t.} \quad \sum_{k \in K} e_{0k} = 0, \tag{A1}$$

$$S_{0ik} = a_{ik}, \quad \forall k \in K, \forall i \mid v_i \in V, \tag{A2}$$

$$e_{ik} \leq C_{ik}, \quad \forall k \in K, \forall i \neq 0 \mid v_i \in \bar{V}, \tag{A3}$$

$$\sum_{i \in P_j} s_{ijk} - \sum_{l \in S_j} s_{jlk} = e_{jk}, \quad \forall k \in K, \quad \forall j \mid v_j \in \bar{V}, \tag{A4}$$

$$\sum_{i \in P_j} s_{ijk} - e_{jk} = t_{jk}, \quad \forall k \in K, \quad \forall j \mid v_j \in \{V \mid C_{jk} > 0\}, \tag{A5}$$

$$\sum_{k \in K} s_{ijk} \le Y_{ij}, \quad \forall i, j \mid (v_i, v_j) \in L, \tag{A6}$$

$$s_{ijk} \le S_{ijk}, \quad \forall k \in K, \forall i, j \mid (v_i, v_j) \in L, \tag{A7}$$

$$\sum_{g} \sum_{r \in R^g} z_{ij}^{rg} = 1, \quad \forall i, j \mid (v_i, v_j) \in L, \tag{A8}$$

$$\sum_{g} \sum_{r \in R^g} y_{ij}^{rg} = \sum_{k \in K} s_{ijk}, \quad \forall i, j \mid (v_i, v_j) \in L, \tag{A9}$$

$$y_{ij}^{rg} \le U^{rg} \cdot z_{ij}^{rg}, \quad \forall r, g, \quad \forall i, j \mid (v_i, v_j) \in L,$$

$$y_{ij}^{rg} \ge L^{rg} \cdot z_{ij}^{rg}, \quad \forall r, g, \quad \forall i, j \mid (v_i, v_j) \in L, \tag{A10}$$

$$t_{ik} - t_{ik}^{OT} + u \cdot C_{ik} \cdot \alpha_{ik}^{OT} \le u \cdot C_{ik}, \quad \forall k \in K, \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A11}$$

$$t_{ik}^{OT} \ge u \cdot C_{ik} \cdot \alpha_{ik}^{OT}, \quad \forall k \in K, \quad \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A12}$$

$$t_{ik}^{OT} \le M \cdot \alpha_{ik}^{OT}, \quad \forall k \in K, \quad \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A13}$$

$$e_{ik}^{LW} \le W_{ik} \cdot \beta_{ik}^{LW}, \quad \forall k \in K, \quad \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A14}$$

$$e_{ik} - e_{ik}^{LW} \ge W_{ik} \cdot (1 - \beta_{ik}^{LW}), \quad \forall k \in K, \quad \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A15}$$

$$e_{ik} - e_{ik}^{LW} + C_{ik} \cdot \beta_{ik}^{LW} \le C_{ik}, \quad \forall k \in K, \quad \forall i \mid v_i \in \{V \mid C_{ik} > 0\}, \tag{A16}$$

$$e_{ik}, s_{ijk}, t_{ik}, y_{ij}^{rg}, t_{ik}^{OT}, e_{ik}^{LW} \ge 0, \quad z_{ij}^{rg}, \alpha_{ik}^{OT}, \beta_{ik}^{LW} \ binary \ge 0. \tag{A17}$$

Our MILP formulation has an integer optimal solution when the values for capacity, demands, and bounds (i.e., Y_{ij}, S_{ijk}, L^{rg}, and U^{rg}) are also integer. We do not need to force the integrality of decision variables e_{ik}, s_{ijk}, t_{ik} (and consequently of y_{ij}^{rg}, t_{ik}^{OT}, e_{ik}^{LW}) because of the special structural properties resulting from constraints (A1–A7). This subproblem is a separable multicommodity flow problem with arc capacity, with the unimodularity and separability nice properties (Bertsekas 1998). Unfortunately, the separability property is lost in the RNCL problem formulation, making its exact resolution difficult.

When the MILP is solved, planners obtain a production and transportation plan. At this point, and as the last step to fully specify the plan, we estimate the QoS by the AGA indicator using the following expression:

$$\text{AGA} = \sum_{k \in K} \left[\sum_{(v_i, v_j) \in L} s_{ijk} + \sum_{v_i \in V} s_{i(N+1)k} \right] \Bigg/ \sum_{k \in K} \sum_{v_i \in V} a_{ik}. \tag{A18}$$

Appendix B. Sensitivity Analysis Report

The DOE we selected to conduct our tests is a reversed 16-run Plackett-Burman (Wheeler 1989). We generated 160 instances of the planning problem, which we solved using a server with a 2.4 GHz Intel Core2 Quad Q6600 processor, 4 GB of memory, and a Windows XP professional ×64 operating system. We used an optimization engine coded using AMPL v10.1 (Fourer et al. 2003) and resolved using ILOG CPLEX 11.

We used fa to obtain the values for demands as samples of a random variable ($a'_{ik} = a_{ik} \cdot fa \cdot Uniform(0, 2)$), and fc to do so for the installed capacities ($C'_{ik} = Norm(C_{ik}, fc \cdot C_{ik})$), where $fa = 1$, $fc = 1$ are historical values.

We summarize the factors and levels we studied as follows:

- The penalty because of excessive transhipments: p (10, 50, 100) €.
- The threshold that triggers this penalty: $u(1.2, 1.5)$.
- The penalty for inadequate use above the minimum workload: $p^{\text{low}}(10, 20, 30)$ €.
- The scope and complexity of the network: *size* (provincial, regional). Two testing maps of RNCL, corresponding to the Huelva province ($G^1 = (V^1, L^1)$), with 110 vertices and 306 links, or to the Andalusia region ($G^2 = (V^2, L^2)$), with more than 400 vertices and almost 2,500 links.
- The variation coefficients used to obtain demand samples: a'_{ik}, $fa(1, 1.25)$.
- The variation coefficients used to obtain capacity samples: C'_{ik}, $fc(0.1, 0.2)$.
- The stop time for the MILP: *Tlimit* (900, 1,200, 1,800) seconds.

We measured the following responses:

- The value of the objective function: *VTotal_Cost*.
- The AGA indicator: *VAga*.
- The total outsourcing cost output: *VExtern*.
- The gap to the optimal solution reported by the solver software, *VOpt_mipgap*.

Finally, we analyzed the experimental results using three ANOVA techniques. The first technique is a single-factor (SF) analysis of variance (i.e., a one-way ANOVA) to evaluate significant results for each response. The second technique is a single-degree-of-freedom (SDF) ANOVA to show the influence of each factor on each response. Alternatively, we tracked the progress of responses for the different levels of factors using an analysis-of-means (ANOM) technique.

Table B.1 shows the one-way ANOVA results from which we observe significant effects in all the responses because of the combination of factors (and levels selected for the factors u, p, p^{low}, *size*, *fa*, *fc*, *Tlimit*), not only because of the random error component. Table B.2 shows the results of SDF and ANOM tests. Whenever a significant effect is detected

SF-ANOVA	V_Total_Cost		V_Aga		V_Opt_milpgap		VExtern	
	Responses							
Sum of squares	2.67E+16	5.01E+14	3.61	0.19	3.068	65.41	4.06E+09	2.48E+10
Degree of freedom	15	144	15	144	15	144	15	144
Mean square	1.78E+15	3.48E+12	0.24	0	204.5	0.45	2.71E+08	1.72E+08
F-ratio	**511.4***		**186.2***		**450.3***		**1.57***	
P-value	< 0.001		< 0.001		< 0.001		0.09	
	B	W	B	W	B	W	B	W

Table B.1: We analyzed the factors' effects on responses using experimental design theory; we first looked at significant effects for each response. The table shows one-way ANOVA results for a confidence level of $\alpha = 1$.
Note. **Boldface and asterisk denote statistical significance. B: Between Experiments; W: Within Error.**

	VTotal_cost	*VAga*	*VOpt_mipgap*	*VExtern*
p		0.8 / X	0.1 / X	
p^{low}		0.9 / X	O	
Tlimit		1 / X	0.1 / X	
u			O	
Size	97.1 / X	90.2 / X	97.2 / X	
fa	1.1 / X	1.3 / X	0.4 / X	2.7 / X
fc		0.9 / X	O	9.1 / X

ANOVA / ANOM

Table B.2: We analyzed the factors that are responsible for the response variations we observed. The table comprises the results of SDF ANOVA and ANOM for a confidence level of $\alpha = 1$.

in the SDF test, the contribution of the significant factor to the involved response appears in the upper left corners. Similarly, the ANOM test results appear in the bottom right corners, with an "X" if the results are above the ANOM control boundaries (i.e., the factor is significant) and an "O" if they are close but not above the control boundaries. We interpret the results in the *Sensitivity Analysis* section.

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Verification Letter

Antonio Nunez-Roldan, M.D. Ph.D., Manager, Plan Regional de Laboratorios Clinicos, Sistema Sanitario Público Andaluz, Sevilla, Spain writes:

“In our organization we are in charge of planning issues in the context of Andalusian Public Health Services. We state that we are using the graphical user-interface (GUI) tool presented in the work entitled “A Decision Making Tool for a Regional Network of Clinical Laboratories” (see the enclosed abstract) to support our planning decisions in the Andalusian Regional Network of Clinical Laboratories (RNCL).

“We are about to open a variety of new clinical labs, and the tool is being employed to decide which is the optimal priority. We have to redesign coverage and establish new connections in a very extensive region (up to 8 million people), so changes need to be progressive. In our continuous improvement approach, this tool is assessing us in the adoption of Annual Plans, in which we pursue a balance between the economic point of view (i.e., budget constraints) and the quality of service provided to citizens.

“The adoption of the GUI tool has represented a very noticeable advance in our decision process. We must remark the following features:

- “It is a GUI tool that meets our needs and expectations, which consisted in a user-friendly software tool to make quantitative decisions.
- “User-computer communications is easy, based on a well-known intuitive graphical interface (Google Maps). Thus, our healthcare managers are constructing new scenarios (network maps) by simply interacting with the GUI, for example fixing new settings in some of our Clinical Labs.
- “Later, optimization tools are launched in order to give us the proper Annual Plan, which is the result of solving the new scenario with Operation Research tools, although the process is completely transparent for us.
- “The GUI design ensures that our decision makers can use and reuse existing efforts and knowledge. They are enabled to derive new scenarios (network maps) and, after looking into the desired performance, to archive the solved map for later use.
- “Graphical comparison between saved solved maps is supported as well. We compare scenarios to choose the one to be implemented among them.

“With quantitative support for decisions, the coordination tasks inside the Primary Care public network is being easier. We are proud to announce that big savings are resulting just in the first year (2009), reducing outsourcing costs above a 15 percent in the first six months. This is a result of the new coordination paradigm, which is strongly related with our forecasting of demands and with the ability to set the proper workload (productions levels) to each Clinical Lab.

“As a conclusion, we verify the actual use of the GUI tool and its resulting benefits in the adoption of the better Annual Plans in the Andalusian Regional Network of Clinical Laboratories.”

Jose L. Andrade-Pineda is a telecommunications engineer from the University of Seville, where he belongs to the Industrial Management Research Group. As a researcher in this group, he has participated in several public and privately-funded projects on the optimization of decisions for healthcare management. He has published a number of contributions in conferences regarding the outcome of these projects.

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